NETWORKS AND ENERGY TRANSITIONS

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NETWORKS AND ENERGY TRANSITIONS

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To my parents, for their unconditional support, belief, patience, advice, and love.

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SUMMARY

This dissertation reflects on strategies for utilizing networks to catalyze a low-carbon energy transition. In particular, I focus on the role of networks for two policy strategies: (i) switching to alternative, low-carbon energy technologies, and (ii) reducing consumption of carbon-intensive, fossil fuel energy resources. Chapter 2 of this dissertation uses historical energy transitions to argue networks complicate prescriptive policy design. In particular, we illustrate the nature of the underlying technologies used to covert physical fuel inputs into energy services structures interactions between markets. The interconnections between markets, in turn, creates complex feedback loops that lead to simultaneous changes across the entire economy. We explore how these feedback loops impact energy efficiency policy in more detail in chapter 4. Chapter 3 investigates the role of networks in proliferating the diffusion of low-carbon energy technologies. We provide evidence that network formation is critical for the early success of emerging low-carbon innovations. When networks form at this early stage of the technology life cycle, they provide a platform for information exchange between early and future adopters, leading to lower search, transaction, and operational costs for future adopters. Lastly, in chapter 4, we develop a theoretical model that embeds industrial, energy efficiency improvements within a network setting to understand how interconnections between markets affects the outcomes of sector-specific low-carbon energy policy. Energy efficiency is often touted as a cure-all policy measure to reduce dependence on carbon intensive, fossil fuel resources. However, when markets are connected by the economy's production network, the outcome of energy efficiency policy is highly uncertain. Using a combination of theoretical and numerical analyses, we illustrate the structure of the economy's production network shapes the change in aggregate energy consumption following a sector-specific energy efficiency improvement.

CHAPTER 1
INTRODUCTION

Networks are the basis for a variety of social and economic activities within society. Social networks, for instance, have important implications for the way information flows between individuals, firms, and institutions. Economic networks, for example, shape the organization of production and the transmission of shocks between firms and sectors in the economy. Given the ubiquitous nature of networks, understanding how behavior changes within a networked setting is critical for designing, implementing, and evaluating policies promoting the transition to a low-carbon energy system.

Transitioning to a low-carbon energy system can be achieved through either the adoption of low-carbon energy technologies or by reducing consumption of carbon-intensive fossil fuel resources. In this dissertation, I explore how networks can be incorporated in both of these strategies to facilitate the low-carbon energy transition. In chapter 2, my coauthors and I synthesize the literature on energy system transitions to construct a stylized framework for evaluating energy system transitions [1]. Our framework builds from existing system-level perspectives on energy transitions to emphasize the role of markets and rational choice. By doing so, we advance a new perspective for evaluating alternative policy strategies promoting a low-carbon energy system transition.

Our energy-service system framework provides a simple scaffolding for constructing low-carbon energy policy from the ground up. We show the technological configuration of an energy system, namely the process by which raw fuel inputs are converted into useful energy-services, structures the interactions of markets within the economy. Even though fuel inputs, technologies, and energy services have evolved over time, the linear process of producing energy services has remained unchanged and thus gives a baseline for evaluating how energy system transitions unfold from a market perspective.

Using historical energy transitions as a guide, we illustrate the networked nature of markets create complex, feedback loops, rendering prescriptive policy design all the more difficult. Markets interact both within and across prevailing technological configurations. Hence, policy actions within a single market will cascade to other markets, either reinforcing or weakening prevailing technological configurations. Our energy-service system framework provides policymakers with the necessary perspective to leverage existing interactions between markets to tip the scales in favor of low-carbon energy sources and technologies.

The transition to a low-carbon economy is hindered by market and institutional barriers that limit the diffusion of low-carbon technologies. Traditional policy interventions either rely on research subsidies or tax incentives to overcome barriers to commercialization and spur investment in these areas. However, the uncertainty with respect to a technology's performance or reliability is not addressed by these traditional policy instruments. Chapter 3 of this dissertation explores how experimentation, learning, and social networks influence the diffusion of breakthrough, low-carbon innovations.

In cases where uncertainty acts as a barrier, both public and private actors may implement pilot and demonstration (P&D) projects, deploying the technology at reduced scale, to remediate this uncertainty. We investigate the impact of P&D projects on adoption of green building technology and unpack the mechanisms driving the observed impacts. We find P&D projects for a popular green building standard increased local green building adoption rates between 5-12 percent. We find this effect is robust to alternative models and assumptions.

We further explore whether the positive impact of P&D projects is driven by herding behavior or learning externalities. From a policy perspective, the objective of a P&D project is to reveal new information about the performance and reliability of a given technology. To the extent new information generated by experimentation might spillover to potential adopters, the social benefits created by these information externalities may warrant additional investments in P&D projects. This is particularly true in cases where information dissemination is an objective. Because of this, we unpack the main results of our analysis to determine whether information spillovers might be driving adoption.

Additional tests indicate adoption may be driven by learning externalities created by P&D projects. First, we illustrate that adoption increases at a higher rate when P&D projects utilize more refined technologies. When P&D projects undergo sequential iterations, stakeholders can improve experimental outcomes by building on successes and refining failures until a technology reaches a marketable stage [2]. This implies that later P&D projects should have a more pronounced impact on adoption if information externalities are the mechanism driving diffusion. Second, we demonstrate that projects exposed to the construction of a P&D project have a 9-12 percent shorter implementation time. One interpretation of this finding is that P&D projects contribute to the formation of supplier and knowledge sharing networks. In particular, reduced project completion times after exposure may indicate non-participating organizations connect with suppliers involved in the P&D project and knowledge regarding best practices was transferred between P&D stakeholders and non-participating organizations.

Another approach for transitioning to a low-carbon economy is to reduce consumption of fossil fuel energy resources. However, many policies in this domain, such as carbon taxes, receive substantial political backlash due to the possibility they might reduce economic growth or drive unemployment within critical sectors in the economy. For these reasons, energy efficiency policy is often touted as a cure-all policy strategy for reducing fossil fuel consumption, while simultaneously promoting economic growth through the more productive use of scarce energy resources.

Over the past century, global energy productivity has increased by more than two-fold over the past century. Breakthrough innovations in common energy services, such as lighting, heating, transportation, and power, have contributed to this increased productivity. However, at the same time, global energy consumption has drastically increased, and the impact of energy efficiency on global energy consumption remains an open question. In chapter 4, we explore the underlying economic mechanisms that connect energy efficiency improvements at a micro-scale, i.e. at the level of individual energy service technologies, and changes in aggregate energy consumption.

The focus of chapter 4 is on the relationship between the economy's aggregate energy consumption and its production network. Production networks reflect the degree of interdependence between sectors in the economy, and the structure of the interconnections between sectors has important implications for how idiosyncratic, microeconomic shocks transmit between sectors and affect aggregate economic outcomes. Because the structure of the economy's production network evolves over space and time, the economic impacts of the same sectoral shocks may differ substantially across regions and over time, even though economic fundamentals, such as gross output and employment, remain constant.

This paper is the first to study how variation in regional economic responses to technological productivity shocks relates to the structure of each economy's underlying production network. We study this phenomenon in the context of industrial, energy efficiency shocks. Using a general equilibrium framework, we show how the structure of the economy's production network shapes aggregate energy production following improvements in the efficiency of energy service technologies. In particular, we illustrate that, for two economies with the same attributes, differences in the systemic importance of the sector experiencing the energy efficiency shock is sufficient to generate variation in aggregate, equilibrium energy production across the two economies.

My analysis proceeds in four steps. First, we develop a general equilibrium model that embeds energy efficiency within a production network to determine the theoretical economic mechanisms that connect micro-scale energy efficiency improvements to aggregate economic outcomes. From the comparative statics of the model, we find the change in equilibrium energy production following the efficiency shock can be decomposed into a price, growth, and composition channel.

Second, I further distinguish each equilibrium channel into a network-driven and direct component. Using this distinction, we construct a simple statistic for quantifying the impact of the economys production network on the change in equilibrium energy production from the energy efficiency shock, what we refer to as the energy savings multiplier.

Third, to provide initial estimates of the practical importance of the energy savings multiplier, we calibrate the parameters of the theoretical model to simulate the change in energy production from a 10% energy efficiency shock applied to each US state. The results of the simulation suggest state-level, energy output elasticities are highly heterogeneous, and re-allocation of intermediate inputs within the economys supply chains directly impact the rebound effect from energy efficiency improvements.

Fourth, we illustrate the magnitude of the energy savings multiplier is directly related to the network centrality of the sector experiencing the energy efficiency improvement. This finding suggests that variations in the underlying structure of regional production networks are sufficient to drive heterogeneity regional economic outcomes following a technological productivity shock.

CHAPTER 2

AN ENERGY-SERVICE SYSTEM FRAMEWORK

The following chapter is a reprint of a published paper:

Blackburn, C., Harding, A., Moreno-Cruz, J. (2017). Toward Deep-Decarbonization: an Energy-Service System Framework. *Current Sustainable/Renewable Energy Reports*, 4(4), 181-190.

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2.1 Motivation

Despite contemporary efforts to mitigate risks posed by global climate change, emissions of anthropogenic greenhouse gases have reached their highest levels in recorded history and show no immediate indication of slowing down on a global scale [3]. From a policy perspective, reducing greenhouse gas emissions can be achieved by either switching to low-carbon technologies or reducing the amount of fossil fuel energy consumed [4, 5, 6]. The scale of environmental risks, however, necessitates monumental changes in both social and technological systems to avoid significant environmental degradation [7]. This encompasses changes in energy use, innovation and development of low-carbon technologies, and broader changes in social, political, and economic institutions.

Relieving the environment of the stressors introduced by global reliance on fossil fuels requires the orchestration of a system-wide transition to a deep-decarbonized energy system. Historically, energy transitions occur over several decades as key transformational processes unfold and realign; a future transition to a decarbonized energy system is likely to be prolonged without additional assertive guidance and direction. Historical analyses illustrate the complexity of energy system transitions using a comprehensive qualitative framework, known as the multi-level perspective; however, the flexibility and comprehensiveness of this framework limits identification of the driving forces behind energy system transitions, limiting any attempt for policy prescription.

Driven by the inherent complexity of energy systems, analysts and policy makers generally rely on historical evidence and quantitative techniques for evaluating the potential impact of public policy on energy technology and fuel substitution, including the impact on broader market processes. In recent years, advances in computing power, data availability, and algorithmic design have permitted use of increasingly complex simulation and optimization techniques in the evaluation of energy system transitions. Specifically, a general class of models known as energy-economy models augments existing historical energy transitions studies by approaching energy transition analysis using quantitative models that combine energy resource extraction, distribution, and consumption into a single framework. While these models have evolved over time to account for more realistic scenarios, quantitative approaches still fall short in capturing the full range of complex interactions between modern energy and market systems [8, 9].

Fundamentally, an energy system is a complex web of relationships between natural resources, physical infrastructure, production systems, scientific knowledge, and consumer practices. Changes in one component can influence the entire system in highly non-linear and unpredictable ways. Hence, steering the transition to a global, low-carbon energy system will require better knowledge of the correct levers to pull and by how much to pull them. The purpose of this review is to provide a unified framework that complements both qualitative and quantitative approaches for studying energy transitions. Motivated by this framework, we argue swift and expansive policy measures are needed to hasten global decarbonization and current policy-oriented studies tend to miss the mark on the importance of scale, complementarities, and feedbacks in energy systems [10, 11, 12, 13].

The paper proceeds as follows. Section 2.2 introduces system-level analyses of energy transitions, primarily focusing on the multi-level perspective literature. Section 2.3 introduces the energy-service system framework using examples from the literature. We illustrate in section 2.4 how government policy can guide low-carbon technological change in an industrializing world. In section 2.5, we provide a brief overview of energy-economy models and their benefits and limitations. Section 2.6 concludes.

2.2 The System-Level Approach

A variety of system-level perspectives have been developed to understand and frame the dynamic interrelationships between social, technological, and natural systems [14, 15, 16]. Arguably, the most commonly used framework in the historical energy transitions literature is the multi-level perspective (MLP). The MLP has been applied to analyze several technological transitions, e.g., the transition to steam ships, automobiles, and renewable energy technologies [14, 17, 18, 19, 20].

The MLP organizes social and technological institutions into hierarchical constructs known as niches, regimes, and landscapes. Niches are the "protective spaces that insulate entrant innovations from the competitive pressures of prevailing technological configurations [21, 22, 23]. Radical innovations occurring at the niche level are the sources of disruption that can potentially de-stabilize incumbent technologies. These protected niche markets permit innovations to develop to a point of cost competitiveness with incumbent technologies, increasing the possibility of a transition [14].

Regimes represent the purposeful alignment of physical and institutional configurations to satisfy a particular societal function. The mutual interdependency that results from alignment of these configurations tends to reinforce prevailing technological trajectories via path-dependent processes, a key feature of the modern fossil-fuel-based energy system [24, 25, 26]. For niche market innovations to lead to a regime-level shift, innovative forces must be strong enough to push society to alternative pathways [27]. These regimes exert pressure on the lower, niche levels that lead to the development of radical innovations [28]. Importantly, technological transitions are characterized by shifts occurring at the regime level.

Landscapes are the macro-level, exogenous trends that exert pressures on prevailing regimes and niches [28]. A couple examples of landscape forces are demographic trends and environmental integrity. Changes at the landscape level can lead to pressure on regimes and niches falling under the landscapes umbrella of influence. Due to their size, landscapes take longer to transition than regimes or niches.

While the MLP is a flexible, comprehensive approach for studying energy transitions, some researchers have criticized the MLP for neglecting the role of consumer choice, government action, and entrepreneurship in technological transitions [16, 29]. Even though the MLP allows for the existence of markets as “rulemaking institutions, which guide and reinforce prevailing regimes, rational decision making is underdeveloped in the MLP [28, 30, 31]. Thus, when market systems do not account for the environmental damages created by a fossil-fuel intensive energy regime, the MLP is a particularly silent source for understanding the appropriate pathways to achieve broader energy system transformations.

When it comes to managing the transition to the low- carbon economy, the failure of free-market institutions to provide adequate incentives for low-carbon technology adoption and consumption motivates the need for government intervention [32]. Consequently, unlike previous transitions, disruption of the technological trajectory of the entrenched fossil-fuel energy regime will require a beautifully orchestrat- ed symphony of market reform mechanisms. Given the MLP is silent on the issue of market failures, an important question arises, what are the channels through which markets, policy institutions, and technology could drive the transition to a low-carbon energy system?

We address this shortcoming of the MLP approach by de- vising a framework that not only considers the technological configuration of an energy system, but its interaction with the prevailing market system. To differentiate this framework from the MLP, we introduce the concept of an energy-service system. An energy-service system represents the observed set of methods and designs that produce socially desirable forms of energy and the market systems that influence them [16, 33]. This interpretation is useful because the technological configuration of an energy system is independent of prevailing niches, regimes, or landscapes and provides a constant stan- dard for comparison across time. Additionally, this framework aligns with recent evidence that suggests energy transitions have largely been catalyzed by novel combinations of energy sources and technologies to provide cheaper energy services to society [34].

2.3 The Energy-Service System Model

The technological configuration of an energy system is comprised of the primary energy sources and conversion technologies needed to produce a valued energy service, such as heat, power, or lighting [35]. Although seemingly more complex systems have emerged over time, this underlying structure has remained unchanged. By analyzing the technological configuration of an energy system together with the market systems in which transactions take place, i.e., an energy-service system, the framework we present below has the potential to inform on aspects of the low-carbon transition where the MLP approach is silent.

The core logic of the energy-service system model is that decisions are costly, and thus the source of change in this model is in the market systems ability to alter the relative cost and benefits of a low-carbon energy system versus maintaining the status quo. A market system (markets) is a complex network of buyers and sellers who trade goods and services with each other. Like other markets, in the market system for energy, interactions between the supply-side and the demand- side determine the pricing of goods and services and the allocation of scarce resources among agents. Ultimately, market prices provide the incentives that guide decision-making and give rise to the technological configurations found in society throughout time. However, prices do not capture the costs of environmental degra-

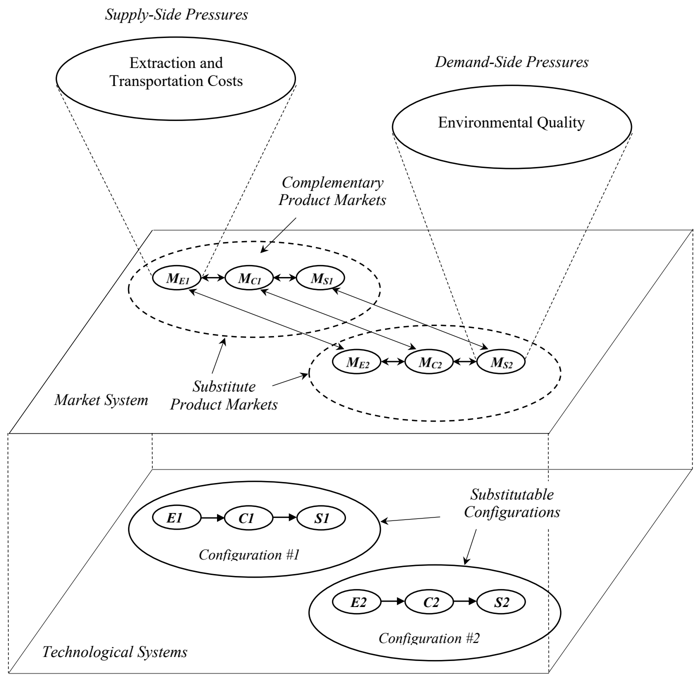


Figure 2.1: The Energy-Service System

dation and are lower than a welfare-maximizing market institution would dictate. Hence, without additional correction to these failures, only scarcity is priced by the markets, providing little incentive to de-carbonize the global energy system.

While most energy systems are comprised of multiple subsystems, the energy-service system framework presented in this paper focuses on the relationship between energy technologies and market systems. These relationships are summarized in Figure 2.1. This figure is adapted from the multi-level perspective hierarchy. The lowest level of the system represents the technological configuration of an energy system. In this level, alternative technological configurations combine primary energy sources, denoted as $E1$ and $E2$, with conversion technologies, $C1$ and $C2$, to produce an energy service $S1$ and $S2$, respectively.

The boundaries of each technology are represented by the circles. Each component of the configurations is linked with the respective markets in the top layer of the figure. Markets for the components are denoted by M. Markets that are present within the boundaries of a technological configuration are linked based on complementary relationships.

However, the connections between markets can cross over these boundaries because of the substitutable nature of the two technological configurations. Finally, supply-side and demand-side pressures influence the outcomes of the markets for the technological components.

The technological configuration of an energy system is made up of energy sources, conversion technologies, and energy services. Energy sources are combined with conversion technologies to provide useful energy services to consumers. The market system is composed of a market for each component of a technological configuration. These markets interact directly with each other through social and technological institutions, as highlighted by the direct linkages between them. Most importantly, however, these markets interact indirectly with each other through the structure of the technological system, where markets within a configuration are complementary and markets across configurations are substitutes.

At the top level of the system, supply-side and demand-side pressures are exerted on the energy-service system. For example, on the supply-side, extraction costs and transportation costs exert pressures on existing markets by expanding the economic abundance of an energy source [36]. On the demand-side, preferences for higher quality fuels and environmentally friendly technologies introduce pressures for the development of new products and technologies. Given the interlinked structure of the technological system, information between markets flows either downstream from supply-side pressures or upstream from demand-side pressures, such that a change in any one component, under the right conditions, can alter the entire system state. In the next subsections, we introduce some examples of these pressures and frame them in the energy-service system framework.

2.3.1 Examples of Supply-Side Pressures

At the turn of the eighteenth century, coal mining in Britain relied on animal and human power to pump water from mines, where the latter was an expensive option given the high wage rates in Britain at the time [37, 38]. This likely incentivized coal producers to adopt the Newcomen and Watt engines in the eighteenth century. Referring to Figure 2.1, the introduction of steam engines represented a supply-side shock that allowed producers to reach deeper reserves of coal ($E1$) at a lower cost [37]. This affected the coal market ($ME1$) by reducing the relative cost of coal to alternative energy sources, such as wood ($E2$). The new information about the relative price of coal to biomass then translated to the market for conversion technologies, given the connections in 2.1. In the market for conversion technologies ($MC1$), coal utilizing technologies ($C1$) gained an advantage over competing technologies ($C2$) leading to higher adoption rates. Ultimately, these feedback channels led to a larger market for a coal-based energy-service system after the supply-side shock induced a lower price for coal-based energy services ($S1$).

Similarly, the current shale gas revolution, driven by innovations in horizontal drilling and hydraulic fracturing techniques, has increased the natural gas supply in the USA to nearly 3 trillion cubic feet. Referencing Figure 2.1, the shale gas revolution has essentially followed a similar process as the coal revolution in the UK. Innovation occurring in the supply-side of the market ($ME1$) has lowered the relative price of natural gas, which in turn has reduced the price of generating electricity from natural gas sources ($MC1$), leading to more widespread adoption of natural gas generation technologies [39]. Another supply-side pressure on the market system is variations in transportation costs. Traditionally, energy-service systems have relied on the natural resources readily available to humankind. Where large-scale transportation systems are either non-existent or transportation is too costly, the energy sources used in energy-service systems are constrained by the proximity of consumers to these sources [40]. In the early periods of human development, fire-making techniques relied on local floral growth to provide valuable services such as heating and lighting [41, 42]. In a modern context, impoverished households in rural China with limited access to energy infrastructure rely on local energy sources, such as wood, straw, and biogas, to satisfy a variety of household functions [43]. Hence, the cost of accessing energy sources weighs heavily on the choice of energy-service systems.

The role of transportation costs is also evident in the co- development of energy and industry infrastructure. In the USA, when hydroelectric plants were developed, local industries benefited from access to cheaper, higher quality electricity. As long-distance transmission lines and coal and natural gas plants spread throughout the USA, being near hydroelectric plants was no longer needed; in other words, industries were no longer tied to the location of power. This allowed industries to locate closer to other input sources, increasing industrial productivity [44]. Similarly, in the sixteenth century, when coal was introduced in England to replace wood, the location of economic activity moved north, closer to the coal sources. However, as canals and railroads spread through the UK, industries were no longer tied to the location of energy sources, and they began to locate in places that offered comparative advantage in other dimensions, e.g., access to markets [45].

As shown in these examples, pressures originate in the energy source market and propagate downstream to energy- service markets, lowering the energy service price. Because conversion technologies are tied to specific energy sources, the lower energy service price encourages adoption of the conversion technology, creating positive feedback between complementary markets. As the examples above suggest, for deep de-carbonization, supply-side innovations are necessary to make low-carbon technologies cost-competitive with fossil fuel alternatives [46].

2.3.2 Examples of Demand-Side Pressures

In the energy-service system, demand for energy services translates into a demand for energy sources due to the techno- logical configuration of the system. Like the supply of energy sources discussed above, there are many factors that influence the demand for energy services. One demand-side pressure highlighted in the literature is the quality of an energy service. Historically, as global real income increased, both producers and consumers developed preferences for higher quality fuels, and these evolving preferences ultimately shaped the configuration of the energy-service systems in place in the modern world. Presently, the environmental quality of an energy service is most relevant for a low-carbon transition. If a service is of higher environmental quality, in that it produces less environmental externalities, ceteris paribus there will be a larger market for that good when consumers have a higher willingness to pay for environmental quality.

Energy sources differ in their chemical composition and, subsequently, in their energy and carbon densities. Historically, these differences have influenced the adoption of energy sources in different ways. Starting with bread and beer making, the use of coal soon spread to glass-making and eventually iron and steel. In the eighteenth and nineteenth century iron and steel industries, coals displacement of bio- mass energy sources was, in part, driven by coals advantages in production, storage, and transportation due to its higher volumetric energy content [47, 48]. However, broad diffusion of coal in iron and steel production was limited until the introduction of quality control techniques in the middle-to-late eighteenth century.

The story is similar for urban coal consumption during Londons population boom in the early-to-middle sixteenth century. Rapid population growth in the city strained the local supply of wood fuel and necessitated transportation of wood from greater distances, thus leading to a doubling of the price of wood per unit of energy [49, 50]. Coupled with the relative advantages offered by coals energy content, which translated into lower transportation costs, the relative price of coal was much cheaper than that of wood fuel in the late sixteenth century. However, widespread diffusion was limited until significant innovation in housing design, mainly after the introduction of chimneys and grates, took hold in early the seventeenth century [37, 38]. Showing the long lasting effects of seemingly minor modifications in society, inexpensive coal at the time encouraged expansion of inefficient building designs based on coal, which still persist today [51].

Coals relative chemical advantage helped fuel the transition from biomass to coal in the iron and steel industries during Britains energy transition, but with fossil fuels, higher chemical energy density is associated with a higher carbon density. In the case of coal, high-carbon content acted as a limiting factor in its expansion and diffusion in some sectors. For example, as coal gained prominence over wood fuel in London for residential heating services, the city experienced a drastic decline in local air quality, which likely increased mortality rates in the city [52, 53]. During this time, the market system provided little incentives to switch to higher quality fuel sources, since cleaner energy sources, such as anthracite coal, commanded a higher price in the market. It was not until anthracite coal became cost effective that energy-service systems were designed to utilize this fuel source. The urgency of the future energy transition toward a decarbonized system requires swift, coordinated action to incorporate environmental considerations in the daily choices of individuals in society.

By discussing the literature through the lens of the techno- logical configuration of the energy system in congruence with the respective market system, an energy-service framework emerges. Through this framework, overcoming market failures and de-carbonizing energy-service systems requires assertive pressures to be applied to the market system. When pressures are applied in one market, the technological configuration of the system re-directs the flow to affect the whole system. Thus, by using the energy-service system as shown in Figure 2.1, policymakers can identify where to apply pressure and, more accurately, determine how much pressure is required to create positive feedbacks throughout the system.

2.4 Designing Policy for the Future

Broadly, the future low-carbon energy transition will require two distinct regime shifts: (i) a shift of post-industrialized, stable regimes in developed countries and (ii) a shift of emerging, possibly more flexible, regimes in developing countries. These two broad categories of regimes have historically differed in both the availability and supply of energy, the necessary supporting infrastructure to exploit energy sources, and their demand for energy services [54]. The barriers that must be overcome to establish a stable, deep-decarbonized energy system depend on the state of the existing regime and exemplify the need for diverse policy measures and international coordination.

2.4.1 Post-Industrialized Economies

Mature regimes in post-industrialized countries are based on the use of fossil fuels and represent a legacy of large-scale investments in complementary energy infrastructure and technology. Scale economies, knowledge spillovers, and network externalities have contributed to mutually reinforcing economic, political, and technological barriers that lock-in fossil-fuel systems [24, 25, 55, 56]. Further, incumbent fossil-fuel technologies may benefit from new ideas introduced by entrant low-carbon technologies and push to remain competitive by developing new business strategies to maintain market share [57, 58]. Hence, the combined forces of lock-in and push-back necessitate a diverse array of policies to destabilize the existing fossil-fuel regime [27].

In post-industrialized economies, if innovators are profit motivated, then innovation activities are directed toward the larger, incumbent fossil-fuel energy-service system, causing further lock-in the fossil-fuel regime in the long run [59]. Additionally, if innovation is the locus of change in the energy-service system model, then destabilizing locked-in, existing fossil fuel regimes will require support for the development of novel, substitute low-carbon technologies. From this perspective, when markets provide little incentives for private research and development (R&D) in low-carbon technologies, governmental institutions can increase investment through policy initiatives that support development of low-carbon technologies.

Considering technical change as an endogenous factor in models used to analyze optimal policy intervention has the potential to greatly change the results of models that treat technical change as an entirely exogenous factor [60]. While economists have begun to analyze optimal policy intervention in a transition to clean technology in the presence of path dependency and directed technical change, this nascent and critically important literature has room to grow [59, 60, 61, 62]. So far, this research has found that a combination of research and development and carbon taxes are critical factors of optimal policy design to overcome lock-in in developed countries and tip the scales in favor of adoption of low-carbon technologies in developing countries. With the correct policy mixture, existing regimes can be destabilized and a new, low-carbon regime can reach a point of positive feedback and stability.

Climate change policy can include many different instruments that are designed to reduce environmental damage. These policies come in two flavors: command-and-control regulations or market-based instruments. Command-and- control regulations mandate producers to meet specific performance targets or invest in particular low-carbon technologies; in contrast, market-based policies, such as cap-and-trade, carbon taxes, or R&D subsidies, establish a specific market price for activities that either contribute to or avoid damaging the environment [32]. Naturally, market-based instruments raise the price of high-carbon sources relative to low-carbon counterparts, which leads to an increase in carbon intensive energy prices. A variety of studies that examine the relationship be- tween climate policy, prices, and innovation find more stringent environmental policy and higher energy prices are followed by a non-trivial increase in low-carbon innovation activities [63, 64, 65, 66]. Additionally, when the outcomes of RD are highly uncertain, which is especially true during the early stages of a technologys lifecycle, government sponsored research, development, and demonstration projects can facilitate the transfer of niche products from basic research to the commercialization phase [67, 68].

If new competition from low-carbon niche technologies forces incumbent fossil fuel technologies to invest in strategies to remain competitive, and the consumer adoption decision is determined by the relative prices of two competing technologies, then diffusion of low-carbon technologies is likely to be a gradual and slow process. Without additional policy support for uptake of low-carbon technologies, fossil fuel technologies may continue to enjoy their relative price advantage as producers seek new ways to improve performance considering the new competition from low-carbon alternatives. Hence, taxes and subsidies can be used to adjust these prices to favor low-carbon technologies and accelerate uptake in the market.

2.4.2 Emerging Economies

World energy consumption is expected to rise by around 5% in the next 25 years, as large countries like China, India, and Russia continue to industrialize and develop [69]. Largely void of large scale, fossil fuel infrastructure, developing countries are not necessarily subject to the same lock-in and push-back forces experienced by countries with mature fossil-fuel markets, infrastructures, and technologies. In contrast, industrializing and developing countries can take advantage of their development status and learn from the successes and failures of early adopters of low-carbon technology and policy to effectively "leap-frog" fossil fuel-based energy systems [70, 71, 72]. However, additional impediments in developing countries, such as weak, or fledgling financial institutions or political corruption, may introduce new frictions for financing of large-scale low-carbon development projects and thus impede progress toward developing a low-carbon energy system [73].

The transfer of low-carbon, environmentally friendly technologies from developed to developing economies is an important feature of international environmental agreements, such as the Kyoto Protocol, but a fiercely debated topic in the recent Paris Climate Agreement [74]. While technology transfer is a somewhat ambiguous terminology, the concept encompasses the transfer of a range of knowledge and physical capital transfers between developed and less developed countries. A few studies have examined the international dif- fusion of environmental technologies. These studies suggest that international transfer of best-practice environmental regulations is a pre-requisite for successful adoption of environmental technologies from the world frontier [63, 75, 76]. For a global, low-carbon energy transition to take hold, energy policy in the developing world must be designed to take advantage of the early stages of development and bypass the entrenchment stage of large-scale, fossil-fuel dependent energy systems [26]. As nations advance in material welfare, market and political institutions also tend to become more inclusive and participatory in their structure; but, in theory, by introducing protectionist, anti-competitive, niche imitation strategies in the early stages of growth, developing nations can exploit frontier technologies to establish new technological regimes and experience more rapid growth rates in early development periods [77, 78]. This is commonly referred to as the "advantage of backwardness" [79]. However, for this strategy to be viable, developing countries must rely on international low-carbon technology transfer as a critical pathway for transitioning emerging regimes to a primarily low-carbon composition.

2.5 Energy-Economy Modeling of Energy Transitions

Due to a dearth of data for historical energy transition analysis, policymakers turn to a variety of quantitative approaches to forecast the impacts of alternative energy policy scenarios on energy resource consumption and technology choice. These approaches fall under a collective classification of models known as energy-economy models. Energy-economy models explicitly model the interactions between energy technologies and market systems and are generally divided into three categories of models according to the detail by which the interactions within the energy-service system are structured. The general classifications are typically divided into (i) bot- tom-up, (ii) top-down, and (iii) hybrid approaches. Overall, these classifications are special cases of the energy-service system framework.

While energy-economy models have increased in detail and sophistication over time, the oldest class of models is known as bottom-up approaches. The bottom-up approach is a partial equilibrium representation of an energy-service sys- tem and features a wide-range of technologies to capture the technological richness of the energy supply-side and demand- side components. Technology and fuel choice is cast as a cost- minimizing optimization programs, such as in the ETA, MARKAL, and MESSAGE models [80]. However, despite the technological richness of these modeling approaches, conventional bottom-up modeling generally neglects finer details regarding consumer behavior and broader market transformation [81, 82, 83]. Hence, application of these models has limited utility in determining the set of optimal policy instruments that would be required for a system-wide push to de-carbonization since, by design, they favor technology-based standards.

In contrast to conventional bottom-up approaches, top-down approaches represent energy market systems in a general equilibrium framework but lack explicit characterization of technological configurations of an energy system found in conventional bottom-up approaches. Top-down approaches tend to approach the energy-service system from an economy-wide perspective, and thus feature a highly aggregated level of analysis at the technological level. In most models, energy technology characteristics and technology adoption decisions are governed by aggregate parameters that proxy substitution between technologies and their characteristics. Governed by the choice of these parameters, aggregate system-wide technological changes do not afford much detail in terms of the microeconomic processes that dictate consumer and firm-level technology choice [60]. Consequently, the top-down approachs focus on aggregate system changes comes at the expense of exploring the impact of alternative policies on substitution between alternative technological configurations of an energy system. Even more, the orientation of top-down models to aggregate market-driven process- es limits policy analysis to market-based instruments [8].

In recent years, many analysts have recognized the limitations of conventional bottom-up and top-down approaches and have developed an alternative approach to bring energy-economy modeling closer to a fully integrated energy-service system framework [84, 85]. This class of modeling known as the hybrid approach combines the technological richness of bottom-up models with the market-oriented perspective of top-down approaches. The result of this combination is a richer characterization of feedback channels between technological and market systems that permits analysis of a broader array of policy instruments, i.e., combinations of technology- push and demand-pull policies. However, due to the intensive data requirements of the hybrid approach, most studies tend to narrowly focus on single sector analysis, e.g., the electricity sector, and neglect heterogeneity across other sectors technology choices [86, 87]. The hybrid energy-economy approach is arguably the most comprehensive quantitative approach for analyzing the role of policy in catalyzing energy transitions. However, most studies focus on single-policy scenarios or single sector impacts. The energy-service system framework exemplifies the need for a broader set of policy instruments to de-carbonize the global energy system. Given the complexity of existing, combined bottom-up and top-down approaches, the energy-service sys- tem framework simplifies the dynamics at work so that policymakers and practitioners can glimpse into the black box of hybrid energy-economy modeling [88].

2.6 Conclusion

The transition to a low-carbon energy system has already been set in motion [20]. Given the urgency of the task, the set of questions for researchers is how to optimally guide the transition, overcome any social and technological impediments, and influence the speed of the transition using policy intervention. Unfortunately, policy analysis is usually narrowly focused on individual sectors or technologies. As economists and policymakers analyze the role of policy intervention in guiding a low-carbon energy system transition, it is important to consider the strong interdependencies established by the energy-service system framework. For deep de-carbonization to occur, policy interventions need to be swift and expansive. While there is a role for incremental efforts, overcoming carbon lock-in and push-back requires a large shock to the system. For these shocks to be most effective, they need to occur on both the supply-side,influencing the markets for energy sources ($ME1$), and on the demand-side, influencing the market for energy services ($MS1$) to be most effective. Subsidies for consumption are needed to pull for a cleaner energy system, but an effective policy portfolio should include taxes and standards for the supply-side so that energy producers begin to push for a decarbonized energy system. Finally, subsidies for innovation need to be all encompassing, creating the incentives to invest in new technologies that would facilitate the transition to a low-carbon energy system.

Going forward, the energy transitions literature must first take stock of where we are in terms of active policies, the development and diffusion of existing low-carbon technologies, as well as continue to study the role that markets play, especially in situations where path dependency is present [89, 90, 91, 92, 93]. Research needs to further its understanding of deep de-carbonization within an energy-service systems framework to hasten the future transitions [94, 95]. In particular, we must identify which limitations are currently present or may arise along the path of transition, such as technological, infra- structure, or labor constraint [96, 97].

CHAPTER 3
DO PILOT AND DEMONSTRATION PROJECTS WORK?

Pilot and demonstration (P&D) projects are commonly deployed to catalyze early adoption of technology, but are poorly understood in terms of mechanism and impact. In this Chapter, we conceptually distinguish unique functions of pilots and demonstrations, then examine whether they accelerate green building adoption. To identify effects of P&Ds on adoption, we develop a *difference-in-difference-in-differences* strategy, exploiting variation in location, technologies, and timing of P&D projects. Results indicate a 12% increase in adoption rates within markets affected by P&D projects. Further analyses examine mechanisms driving this effect. Subsequent results suggest green building demonstration projects create learning externalities, proliferating technology diffusion under certain conditions. Taken together, our results suggest that P&D projects are most effective when they contribute to the formation of collaborative, stakeholder networks where information on best practices can be freely exchanged among network members.

3.1 Introduction

Investment in new technologies may have substantial benefits for firms, their stakeholders, and the environment, but is hindered by uncertainty about the performance of the emergent technology [98]. For durable technologies, resolving uncertainties may be an important strategy to foster market uptake [99, 100, 101]. Traditional policy interventions to catalyze adoption often leverage regulatory mandates or provide financial incentives [102]. Alternatively, policymakers may implement pilot and demonstration (P&D) programs, deploying the technology at reduced scale to remediate uncertainty about the reliability and performance of new technology [2].

P&D programs may serve a critical role in the successful early deployment of emerging technologies. Technology pilots are experimental implementations designed to verify feasibility and assess private benefits of adoption [103]. Demonstration projects are technology showcases that may create information or learning spillovers, mitigating uncertainty about how well a technology aligns with private interests [104]. Despite the use of P&D programs by a wide variety of private firms and public agencies, little work has verified and evaluated their efficacy in increasing technology adoption.[1] This gap is particularly prominent in comparison to the breadth of analysis on research and development stages, where analysis typically identifies conditions of innovation and outcomes of research programs.

We first seek to identify whether P&D programs work, using data from a suite of green building PDs. We investigate the impacts of a suite of green building P&Ds on subsequent local market adoption rates. Our primary identification strategy leverages a *difference-in-difference-in-differences* (DDD) estimation framework to identify the average effect of a green building P&D project on market uptake of green building technology by exploiting quasi-experimental variation across time, location, and technology. Results suggest that, on average, local green building adoption rates increase between 5% and 12% following the completion of a P&D project. This finding is robust to a variety of alternative assumptions and specifications.

Successful P&D programs remediate uncertainties about the performance or feasibility of an emerging technology. While the results identified in the DDD model may be driven

[1] Agencies around the world operate demonstration programs explicitly linked to information-based market failures. These include (i) the World Health Organization's efforts to increase adoption of public health technologies in developing countries (`http://www.who.int/phi/implementation/phi_cewg_meeting/en/`); (ii) the US General Services Administrations program to increase the use of efficient building technologies in government offices (`https://www.gsa.gov/about-us/organization/office-of-governmentwide-policy/office-of-federal-highperformance-buildings/projects-and-research/demonstration-projects`); and (iii) the European Space Agency's initiative to increase applications of space technologies to broader markets (`https://business.esa.int/funding/direct-negotiation-call-for-proposals/demonstration-projects`), to name a few.

by social learning in which information spillovers resolve these uncertainties, herding behavior may also explain the uptick in adoption. Because herding may inadvertently create lock-in around a technology chosen by policymakers, rather than market processes, learning is the preferred P&D outcome which generates the greatest social value. Moreover, while the DDD estimates suggest effects of the project on surrounding markets, it does not capture effects of participant firm experience that that may further drive adoption. We perform subsequent analysis to explore how P&D projects work and unpack some of these channels of effectiveness.

A series of empirical tests collectively informs our understanding of the roles that learning and herding play in the outcomes of P&D programs. First, projects occurring at a later date and deploying more certain technology have a more significant effect on adoption rates when compared to the effects of earlier, more experimental green building P&D projects. This result suggests potential adopters may be updating their private beliefs in response to the demonstrated performance of the new technology, rather than simply imitating the behavior of early adopters. Second, we find the required implementation time is 9-12% lower for organizations local to a green building P&D project. As the construction industry is sensitive to costly project delays, we interpret this reduced implementation time as evidence that stakeholders learn from P&D participation, and may socially influence non-participant neighbors.

This paper contributes to the existing literature in at least three ways. Foremost, we provide empirical strategies to evaluate the extent to which P&D programs foster technology diffusion. Our DDD identification strategy compares variation in green building adoption rates before and after market exposure to P&D projects to adoption trends in untreated markets, and does so for a suite of building technologies. The results estimate the causal effect of a P&D project on the diffusion of green building technologies. By comparison, past P&D literature typically addresses this question qualitatively or evaluates the effects of an individual project on the performance of a technology. For example, Mah, Wu, Ip, and

Hills [105] describe the opportunities and challenges of smart grid P&D projects within regulatory and business-oriented schemas in Japan. Hendry, Harborne, and Brown [106] present dozens of case studies highlighting innovation lessons from solar photovoltaic and wind energy P&D projects in the United States, Japan, and Europe. Hendry and Harborne [107] examine qualitative evidence from wind developments in Denmark to show how P&D projects enhance the overall innovation process. Rather than taking a qualitative approach or assessing P&D effects on private performance, we investigate the role of P&D projects on market adoption of emerging technologies.

Second, we contribute to an burgeoning dialogue on information spillovers from environmental programs. Green technologies often have multiple positive externalities, leading private costs to be less than social benefits and inhibiting optimal levels of adoption. For durable technologies that provide returns over a long time horizon, discounting slows investments in emerging technologies [102]. Information provision appears to be an effective policy intervention that generates positive regional learning externalities for these technologies, such as lighting [108] and garment cleaning [104]. Pollution prevention programs have been shown to be effective when leveraging information spillovers, even absent stringent regulatory measures [109, 110]. We complement these findings by examining how well P&D programs impact adoption in the construction industry, drawing on evidence suggesting an information spillovers mechanism.

Finally, our results give insight on the role of early adopters in the long-run diffusion of a technology [111]. If the lead organization responsible for the P&D project has establishments in multiple locations, organizational learning lowers costs of adoption in subsequent locations [112]. Further, if P&D project stakeholders are highly visible and transparent regarding their experiences with the project, adoption may be seeded in local and new markets through peer effects [113, 114, 115, 116] or social learning [117, 118]. Section 7 discusses opportunities to strategically manage this outcome of P&D programs based on the evidence we provide.

To evaluate whether P&D projects increase adoption of green building technologies and practices, we organize the paper in 7 sections. In section 3.2, we distinguish the characteristics of pilot and demonstration projects, and their roles in fostering market uptake of emerging technologies. We identify potential mechanisms driving the success of P&D projects. Section 3.3 describes the empirical context and data used in the analysis. We utilize data on Leadership in Energy and Environmental Design (LEED) green building ”Pilot” projects, and here introduce the institutional characteristics of LEED that are crucial for our analysis. We present the main empirical strategy, including our identifying assumptions, in Section 3.4. Section 3.5 presents the main results of the study and presents several robustness checks to test our estimates against alternative assumptions and model specifications. Our main results suggest LEED-Pilots projects contribute to a 5-12% increase in quarterly adoption rates of the LEED standard in regions with a completed P&D project. In section 3.6, we explore whether this effect is driven by learning externalities or herding behavior, and present evidence supporting the claim that learning externalities drive adoption of the LEED standard. Lastly, we conclude and provide additional policy implications in section 3.7.

3.2 Conceptual Framework

As new ideas and technologies emerge from basic and applied research, numerous uncertainties inhibit new innovations from reaching market maturity. Unproven technical reliability, uncertain market and institutional receptiveness, and limited organizational and managerial expertise characterize this intermediate stage of the technology lifecycle. Because these uncertainties may limit early investment in emerging technologies [106], this stage is sometimes referred to as the technological “valley of death,” in which socially beneficial technologies fail to diffuse. In this stage, successful market deployment requires a balance of periods of experimentation and market development [2]. Market interventions designed to bridge the valley of death spark diffusion of new technologies by remediating these technical, organizational, market, and institutional uncertainties.

Common interventions promoting new technologies in this stage of development include P&D projects, which implement new technologies at small scale with the goal of reaching broader implementation (market maturity). Pilot projects adopt new technology in experimental fashion, with the intent to learn from the implementation process and refine the technology or verify its best management practices [103]. Due to their experimental nature, pilots often occur within narrow divisions of an organization, such as one department or establishment. Demonstration projects, by contrast, showcase technical feasibility and reliability to broad sets of market actors, often engaging numerous stakeholders to reduce technical and management uncertainties [104, 119]. P&D programs often leverage elements of both pilots and demonstrations, because both interventions aim at inducing learning or reduce uncertainties that otherwise inhibit adoption. However, other mechanisms may drive apparent outcomes, and few econometric evaluations of P&D performance have been conducted. To frame our analysis, we first describe the mechanisms by which P&D projects may increase adoption of emerging technology.

3.2.1 Demonstration projects and social learning

To conduct a demonstration project, a mix of private and public sector actors must coordinate on key project features and execution. Managing the production and dissemination of knowledge within this network is considered essential for the success of demonstrations [2]: demonstrations that contribute to the formation of social and business relationships among members of the project's development team can subsume costs of learning-by-searching for future adopters. The social and business ties established during the demonstration project reduce search and matching frictions by brokering and screening interactions between future adopters, project stakeholders, and input suppliers [120, 121, 122, 123]. The development of a robust knowledge-sharing network facilitates the diffusion of information on product reliability and performance [124], including diffusion to actors not participating in the demonstration.

3.2.2 Social learning versus herding

Even if P&Ds fail to induce learning, an effect on adoption is still plausible. When information fails to diffuse, or when the information is not meaningfully incorporated into the decision making process, herd behavior drives investment in the emerging technology if managers assume that those promoting or involved in the demonstration have better information guiding the decision to adopt [125, 126].This is especially viable when demonstrations actively seek to engage key stakeholders such as market leaders and high-status firms [2]. Importantly, while mimicry drives the diffusion of the technology, herding may lead to lock-in on underperforming technologies. Technology diffusion via learning is the preferred policy outcome as it reveals information that otherwise hinders deployment, thus reducing market barriers for the most efficient available technologies.

3.2.3 Pilot projects and organizational learning

From the outset of a pilot project, those implementing the new technology engage with learning-by-searching and learning-by-doing [127]. As early adopters, organizations actively search for resources useful for technical implementation, and for information regarding likely performance that will later guide project evaluation. This evaluation primes learning-by-doing that enables efficient deployment for later adoption [128]. Thus, organizations learning from participation in a pilot program may have fewer barriers to adoption in other parts of the organization.

At this point, learning-by-interacting may enable additional organizations and stakeholders sharing feedback to diffuse the practice [127, 129, 130], amplifying the effect of the original project through networks of users and stakeholders [131]. After learning from a pilot, a repeat adopter implementing the piloted technology at a different establishment may effectively demonstrate that technology to a new set of stakeholders. In this sense, pilots and demonstrations are conceptually and pragmatically distinct, but are not mutually exclusive when iterated. Our analysis presents evidence from P&Ds in one industry, in terms of social learning, social herding, and organizational learning.

3.3 Empirical Context

The United States Green Building Council (USGBC) certifies buildings that meet its standard for Leadership in Energy and Environmental Design (LEED). The LEED certification system identifies baseline design and performance norms in the construction and real estate industry, and recognizes achievement beyond those norms. Certification is based on improvements to the entire building footprint (including energy, water, materials, land use, and indoor environment) rather than a single characteristic. To attain certification, builders must register, implement high environmental performance technologies, and provide sufficient evidence of these improvements. The certification standard may be flexibly adapted to the particular needs of specific buildings. Though the technologies and practices implemented may vary across buildings, all buildings meet the minimum baseline for each monitored category of environmental technology, and most use advanced planning processes recommended by the USGBC. These best practices are reinforced by a community of professionals trained on the LEED certification process and familiar with how it may be implemented.

3.3.1 LEED Building Standards and Pilot Programs

The USGBC offers separate certification standards for major building categories to recognize the heterogeneous technology demands of different building typologies. For example, the USGBC distinguishes the functional design and practices required by newly constructed buildings from renovations to existing building structures. Standards are further distinguished for several major building uses, namely commercial office, retail, schools, and residential dwellings. These distinct standards are designed to meet the particular needs of each sector of the real estate market and are periodically updated as advances are made in green building technology and practices.

Before introducing a new building standard, the USGBC experiments with different forms of the standard to determine the standard's market viability and to demonstrate the value of the technologies and practices embedded in the standard. After gaining stakeholder support for a version of the standard that appears feasible, the USGBC recruits a limited number of real estate developers, private organizations, and public agencies that volunteer as early adopters. While an organization's decision to volunteer for the pilot program is not random, the location of the eventual LEED-Pilot is independent of the USGBC's recruitment process, as the location decision is determined by the participating organization rather than the USGBC. The LEED-Pilot program constitutes a set of demonstration projects, in that they are conducted by the initial adopters of the new building technology, and the USGBC provides coordination assistance to engage stakeholders in completing the project, with the aim of spreading the standard to others in the building market. These experimental standards are also pilots for the participating firms, who are often interested in adopting the standard at larger scale. Moreover, the name "LEED-Pilot" refers to the USGBCs experimentation with the standard itself, with the final form of the new LEED standard informed by feedback from early adopters of the piloted standard. In this paper, we leverage data on LEED-Pilots, and subsequent LEED registrations in the United States to evaluate the effect of P&D projects fostering adoption of emerging technologies and practices for greener buildings.

3.3.2 Location and Timing of LEED Pilots and Certifications

Adoption of the LEED standard varies over space and time. In Figure 3.1 we show the spatial distribution of LEED certified buildings and LEED-Pilot projects in the contiguous United States. The distribution of registered buildings (black circles) and, notably, LEED-Pilot projects (red circles) in the map is consistent with previous research aligning the

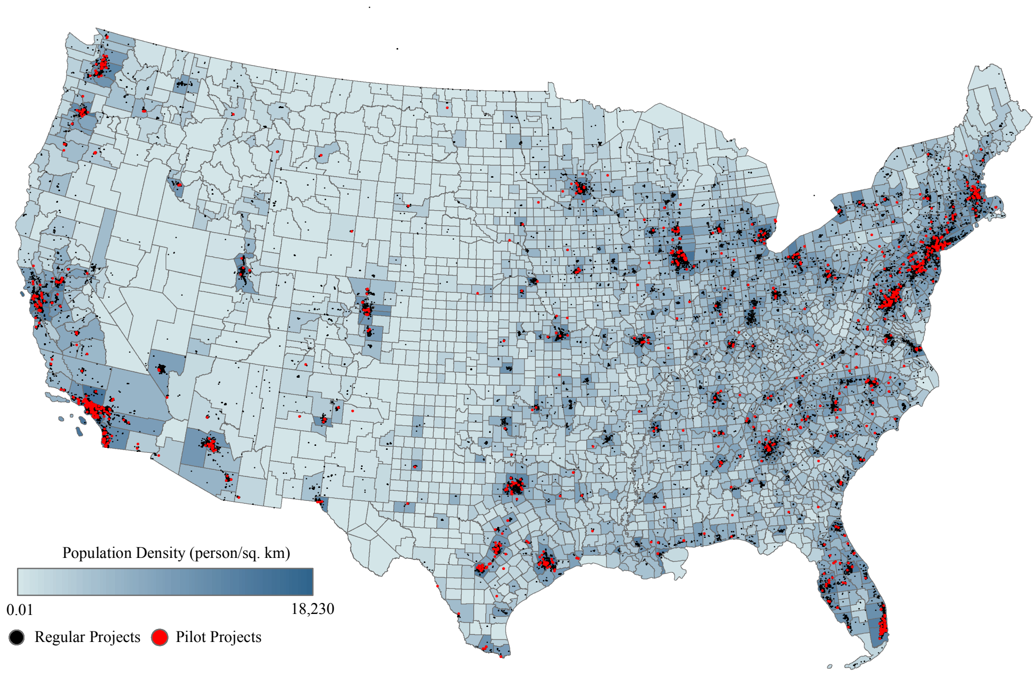
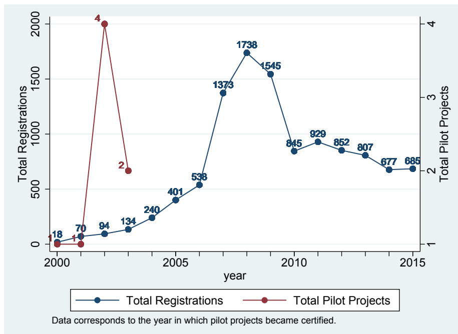


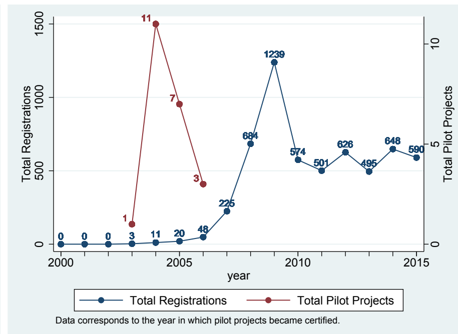
Figure 3.1: Spatial distribution of LEED buildings in the contiguous United States.

location of green building activity with environmental preferences and natural resource demands [132, 133]. Additionally, the frequency and location of green building adoption may closely track regional trends in population growth and urbanization, as illustrated by the clustering of registrations in densely populated areas.

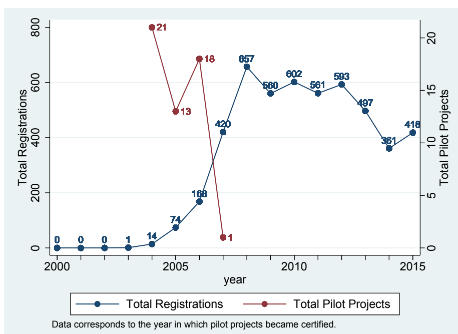
Temporal variation in LEED registrations and LEED-Pilot projects are displayed in Figure 3.2, where we plot the frequency of registrations across years. Examining the figure reveals a close correlation between the completion of LEED-Pilots and registrations for the corresponding building standard. The initial LEED-Pilot program (for New Construction) ran just 8 projects to test and verify the standard. However, subsequent standards have been tested and verified more extensively, with more recent programs (Retail-Commercial Interiors and Retail-New Construction) associated with more than 150 projects each.



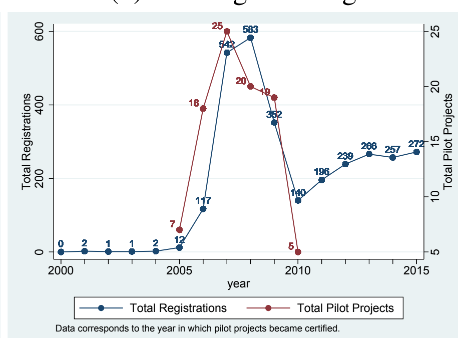
(a) New Construction



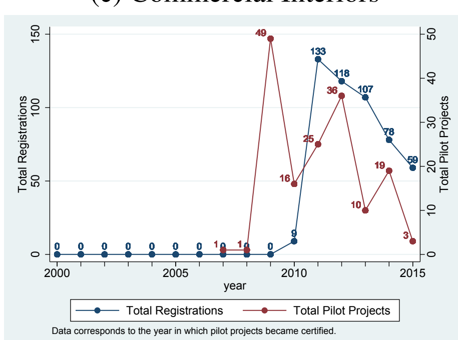
(b) Existing Buildings



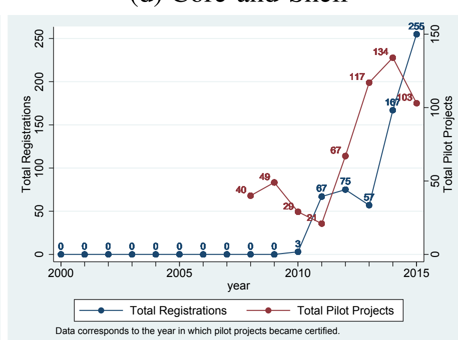
(c) Commercial Interiors



(d) Core-and-Shell



(e) Retail-New Construction



(f) Retail-Commercial Interior

Figure 3.2: Total LEED-Pilot projects and registrations over time

Table 3.1: Adoption statistics for ZIP Codes with and without LEED-Pilot projects

Panel A: Panel Summary Statistics	(I) LEED-Pilot (mean/sd)	(II) No LEED-Pilot (mean/sd)	(III) All (mean/sd)	(IV) Difference (diff/t-stat)
Privately-owned building registrations (R_{zsq})	0.019 (0.178)	0.008 (0.113)	0.008 (0.114)	0.011 (13.986)
Local firm building registrations (R_{zsq}^{local})	0.008 (0.111)	0.004 (0.075)	0.004 (0.076)	0.004 (8.444)
Multiregional firm registrations (R_{zsq}^{multi})	0.010 (0.120)	0.004 (0.079)	0.004 (0.080)	0.007 (12.92)
Publicly-owned building registrations (R_{zsq}^{pub})	0.002 (0.086)	0.004 (0.104)	0.004 (0.104)	-0.002 (-4.974)
Certified private and public building stock (M_{zsq})	0.180 (1.378)	0.089 (0.595)	0.091 (0.617)	0.091 (15.406)
Local firm certified building stock (M_{zsq}^{local})	0.074 (0.633)	0.0326 (0.271)	0.033 (0.281)	0.042 (15.404)
Multiregional firm certified building stock (M_{zsq}^{multi})	0.092 (0.785)	0.032 (0.323)	0.033 (0.281)	0.060 (17.931)
Publicly-owned certified building stock	0.014 (0.170)	0.025 (0.268)	0.025 (0.266)	-0.011 (-15.012)
Observations (ZIP Codes x Standards x Quarters)	55,104	3,071,040	3,126,144	3,126,144
Panel B: Cumulative Summary Statistics (by 2015)				
Total privately-owned building registrations	8.120 (16.860)	2.598 (4.804)	3.144 (7.182)	5.52 (9.25)
Total local firm building registrations	4.015 (8.040)	1.424 (2.586)	1.680 (3.607)	2.59 (9.09)
Total multiregional firm registrations	4.106 (9.466)	1.174 (2.769)	1.464 (4.065)	2.93 (8.74)
Total publicly-owned building registrations	1.615 (3.270)	1.319 (3.484)	1.348 (3.465)	0.30 (2.42)
Total certified private and public building stock	5.086 (10.150)	1.938 (3.266)	2.249 (4.546)	3.15 (8.75)
Total local firm certified building stock	1.852 (4.260)	0.621 (1.434)	0.743 (1.945)	1.23 (8.15)
Total multiregional firm certified building stock	2.406 (5.778)	0.718 (1.730)	0.885 (2.500)	1.69 (8.25)
Total publicly-owned certified building stock	0.827 (1.836)	0.599 (1.544)	0.622 (1.577)	0.23 (3.39)
Observations (ZIP Codes)	805	7,336	8,141	8,141

Notes: Summary statistics are reported for registrations and building stock aggregated to the 5-Digit ZIP code level. Columns (I) – (III) present means in the top row and standard deviation in parentheses. Column (IV) presents the results of Welch's unequal variance t-test for difference in means between Columns (I) and (II). A local firm corresponds to a firm or organization with buildings registered in a single ZIP code. A multiregional firm corresponds to a firm or organization with buildings registered in multiple ZIP codes. Publicly-owned buildings account for municipal, state, and federal buildings.

3.3.3 Data and Summary Statistics

The primary source of data used in this analysis is collected, maintained, and publicly distributed by the USGBC's Green Building Information Gateway. This database contains information on all buildings registered since 2000. The time horizon of our study covers the period 2000-2015, after which the majority of certifications occur in the more recent versions of the standards. Our analysis covers the 44,330 buildings registered within the United States and the six building standards for which pilot program data is available. These ratings systems are Existing Buildings (EB), Commercial Interiors (CI), Core and Shell (CS), New Construction (NC), Retail-New Construction (RNC), and Retail-Commercial Interiors (RCI).

Table 3.1 presents the summary statistics for the central data used in the analysis. Panel A presents the panel summary statistics, corresponding to the typical LEED standard, local markets (measured as 5-digit ZIP code), and quarter. Panel B aggregates the data to present cumulative adoption statistics for the typical LEED standard and local market. Columns (I) and (II) present summary statistics for registrations and building stocks for local markets with and without LEED-Pilot projects, respectively. Column (III) summarizes the key adoption statistics for the entire dataset. Lastly, Column (IV) presents the results of an unequal variances t-test for difference-in-means between Column (I) and Column (II).

A quick inspection of Column (IV) reveals registrations are typically higher in local markets with LEED-Pilots. A naïve interpretation of Column (IV) in Table 3.1 may note the statistically significant increase of green building adoption in local markets with LEED-Pilots as a sign that learning externalities from P&D projects induce greater adoption. However, this correlation may arise from various mechanisms, including location- or technology-specific characteristics, or exogenous trends within markets impacted by a LEED-Pilot. As seen in Figure 3.1, both LEED-Pilots and LEED registrations cluster in major cities, where private organizations may face greater competitive pressures to differentiate. As early market leaders, LEED-Pilot participants may self-select based on unobservable, organizational characteristics, internal motivations, or external recruitment from the USGBC to gain first-mover advantages. Moreover, the selection of particular organizations into the LEED-Pilot program may impact feedback that informs the USGBC's refinement of LEED standards, and may shape adoption trends [111, 134, 113]. Thus, the participant selection plays critical roles for both the pilot and demonstration goals of the LEED-Pilot program. The USGBC actively recruited public and private actors into the LEED-Pilot program, consistent with best practices in the implementation of PDs [2]. Our analysis acknowledges this selection as a critical strategy for successful implementation of P&D programs.

3.4 Empirical Strategy

To investigate average effects of a well-designed P&D program across regional markets, market sectors, and time periods, we develop a reduced-form empirical model to measure the impact of a LEED-Pilot on adoption of the LEED standard.

3.4.1 Identifying Assumption

A simple strategy to estimate the effects of a LEED-Pilot on green building adoption could be to measure the change in adoption rates in markets before and after the completion of a LEED-Pilot, and compare these changes with the change in adoption rates in markets without a LEED-Pilot. This comparison yields the well-known *difference-in-differences* (DD) estimator [135]. Define R as the number of private sector LEED building registrations. In a simplified, conceptual model with two regions (z, z'), and two time periods $(pre, post)$, consider the treated region (the region with a LEED-Pilot project) to be z and the control region as z' (the region without a LEED-Pilot project). The DD estimator can be written as

$$\hat{\beta}^{DD} = \left(\bar{R}_z^{post} - \bar{R}_z^{pre}\right) - \left(\bar{R}_{z'}^{post} - \bar{R}_{z'}^{pre}\right) \tag{3.1}$$

This estimator does not account for the possibility that changes in adoption rates may be driven by idiosyncratic shocks to local markets for green building technologies rather than completion of a LEED-Pilot. For example, Simcoe and Toffel [136] provide evidence that municipal green building policies increase private-sector demand for green building technologies. Specifically, they show that cities with municipal green building policies experience an overall increase in LEED registrations than cities without these procurement policies. If municipal green building policies are implemented around the same time a LEED-Pilot is completed, then the DD estimate erroneously attributes variation in adoption rates to the LEED-Pilot and is biased.

We account for this possibility, as well as any other idiosyncratic shock that raises overall demand for green building technologies, by introducing a third source of variation in the model. Because LEED-Pilot projects constitute the first application of a set of technologies and practices to a particular building typology, we exploit variation in adoption rates within a particular LEED standard (s) as a third source of variation. Our identifying assumption is that, for one particular standard, market location, and time, only a LEED-Pilot project within a particular standard, location, and time is affecting the rate of adoption of a LEED standard. Under this assumption, only mechanisms occuring on the interaction of location, building standards, and time can be interpreted as plausibly exogenous. Given this assumption holds, we can thus exploit quasi-experimental variation in the location, building standard, and timing of LEED-Pilot projects to estimate a causal effect of P&D projects on adoption.

Our empirical strategy boils down to a *difference-in-difference-in-differences* (DDD) estimation that controls for a variety of confounding factors that would otherwise limit our ability to interpret our estimates as causal. For instance, we control for all time-invariant heterogeneity across both geography and building standards, including interactions between them. Additionally, our approach controls for the impact of real estate trends across the United States, within building typologies, and within regional markets that may have affected demand for green building technologies and practices. As a result, the selection of LEED-Pilot participants does not bias our estimates where selection is related to location, time, or market sector. Unobservable characteristics of these early adopters may influence our estimates if participants vary systematically by internal motivations, status, or network relationships. These characteristics are an essential part of all PD programs.

Using the notation from equation 3.1, consider a LEED-Pilot project is conducted in region z for some standard s. We denote untreated standards as s', and, as before, untreated regions as z'. Thus, the DDD estimator is written as

$$\begin{aligned}\hat{\beta} &= \left(\bar{R}^{post}_{z,s} - \bar{R}^{pre}_{z,s}\right) - \left(\bar{R}^{post}_{z',s} - \bar{R}^{pre}_{z',s}\right) - \left(\bar{R}^{post}_{z,s'} - \bar{R}^{pre}_{z,s'}\right) - \left(\bar{R}^{post}_{z',s'} - \bar{R}^{pre}_{z',s'}\right) \\ &= \hat{\beta}^{DD}_{s} - \hat{\beta}^{DD}_{s'} \end{aligned} \tag{3.2}$$

where the parameter $\hat{\beta}^{DD}_{s'}$ represents the DD estimator given in equation 3.1 for untreated (existing) standards. Equation 3.2 measures the extent to which changes in local adoption rates differ from adoption rates in existing standards, following the completion of a LEED-Pilot, relative to the same change in untreated regions. If contemporaneous shocks drove adoption of green building technologies and practices across all building types, then the DDD estimator $\hat{\beta}$ in equation 3.2 would net-out the impact of these shocks. Our identification strategy rests on the assumption that the remaining variation in adoption rates is thus attributable to the effects of the LEED-Pilot project itself. This produces an estimate of the total effect of a LEED-Pilot on local adoption rates, and leaves the mechanisms driving the effect to our later analysis.

3.4.2 Estimating Equation

We estimate the effect of LEED-Pilots on local adoption of the LEED standard using the reduced-form equation

$$\tilde{R}_{zsq} = V_{zsq} + \beta P_{zsq} + \varepsilon_{zsq} \tag{3.3}$$

where the index z corresponds to the 5-digit ZIP codes with at least one LEED registered building to date. The subscript s indexes the LEED standard. Lastly, the index q corresponds to the quarter and year of registrations.

The behavioral outcome of interest in equation 3.3 is adoption of a LEED standard within a 5-digit ZIP code R_{zsq}. For the analysis, we use the number of privately-owned registrations of a LEED standard as a proxy for building adoption. This regional measure is independent of the selection process by which a LEED-Pilot is assigned to an individual firm within the region. Due to a preponderance of zero registrations in the data, the LHS variable $\tilde{R}_{zsq}$ corresponds to the Inverse Hyperbolic Sine (IHS) transformation of quarterly registrations [137, 138].[2]

In the main analysis, we treat the LEED-Pilot variable P_{zsq} as a binary variable taking values

$$P_{zsq} = \begin{cases} 0 & \text{if } q < \tau_{zs}^{cert} \\ 1 & \text{if } q \geq \tau_{zs}^{cert} \end{cases} \tag{3.4}$$

where τ_{zs}^{cert} represents the date a pilot project achieved certification. In locations with multiple LEED-Pilots in the same standard, the variable P_{zsq} represents the completion date of the *first* LEED-Pilot to be certified in a 5-digit ZIP code.

[2]The IHS transformation of quarterly registrations is calculated using the following relation

$$\tilde{R}_{zsq} = \ln\left(R_{zsq} + \left(R_{szq}^2 + 1\right)^{1/2}\right)$$

We use $V_{zsq} = \lambda_q + \delta_z + \gamma_s + \xi_{sq} + \alpha_{zs} + \pi_{zq}$ as shorthand to represent the fixed effects terms in the model. We include a full set of fixed effect and interaction terms to control for potential confounding factors in the analysis. Time period fixed effects λ_q control for time-varying secular patterns in the United States that may have influenced private sector investment in green building technologies, such as fluctuations in real interest rates or federal building standards. We include ZIP code fixed effects δ_z to control for unobserved, time invariant factors that may have influenced adoption of the LEED standard in a particular location, such as local geographic conditions. LEED standard fixed effects γ control for time-invariant heterogeneity across standards or building types.

A full set of dummy variables are included to capture interactions between these three sets of fixed effects. Time-varying shocks within LEED standards are controlled for by ξ_{sq} in equation 3.3. These account for the impact of variations within a LEED standard on adoption across the United States, such as price variations in underlying technologies, aggregate learning-by-doing, or broader awareness of the standard that is exogenous to the LEED Pilots. The term α_{zs} accounts for time-invariant interactions between regional markets and standards. For instance, regional markets with an initial building stock mainly comprised of old, commercial buildings may naturally experience more registrations in the Existing Building standard given the larger initial stock of this building type. We account for time-varying shocks within regional markets with the term π_{zq} in equation 3.3. These interacting dummies control for time-varying factors that influence the propensity for green building adoption within a particular regional market. These time-varying factors include but are not limited to changes in municipal green building policy, variations in environmental preferences, or fluctuations in local real estate market conditions. The parameter of interest in equation 3.3 is β, which measures the average effect of LEED-Pilots on local adoption of a LEED building standard. Our identification of this effect relies on the assumption that, other than what we have already controlled for in equation 3.3, there are no other idiosyncratic shocks occurring around the completion of a LEED-Pilot project that influence local demand for a particular LEED building standard. The parameter β is equivalent to the DDD estimator $\hat{\beta}$ given in equation 3.2, if our identifying assumption holds, and is identified from within ZIP-standard comparisons over time. For P&D projects to successfully induce widespread adoption in local green building markets, LEED-Pilots must have positive and significant effect on registrations within a LEED building standard ($\hat{\beta} > 0$ after estimation).

Self selection of organizations into the LEED-Pilot program may also pose a threat to the validity of our identification strategy. LEED-Pilot participant's decision to volunteer for the program is likely driven by unobserved organizational-level heterogeneity not captured by the fixed effects in the model. This unobserved heterogeneity could bias our estimate of the treatment effect if the location of LEED-Pilot projects is non-random and confounded with adoption propensity. To avoid the selection bias introduced by the voluntary nature of the program, our analysis investigates the impact of LEED-Pilot projects on local adoption of the LEED standard by *non-participating* organizations of the LEED-Pilot program.

By studying the impact of LEED-Pilot projects on non-participant adoption, we mitigate the selection bias introduced by voluntary participation in the pilot program. The assignment of LEED-Pilot projects across locations by a participating organization is independent of the propensity for non-participating organizations to adopt the LEED standard in the same location and building standard. If the USGBC had selected the location of LEED-Pilot projects, for example, they would have selected the most favorable locations for diffusion of the new standard, i.e. where non-participating organizations have stronger incentives to adopt the piloted LEED standard. Under this scenario, our estimate of the effect of LEED-Pilots on adoption would be biased upward.

However, the USGBC does not select the location of LEED-Pilot projects. Instead, the LEED-Pilot program is conducted on a voluntary basis, and the assignment of LEED-Pilot projects across locations is delegated to the volunteering organization. Because of this feature of the program, location decisions are determined by the idiosyncrasies of the participating organizations, and thus the location of LEED-Pilot projects reflects what is most profitable for the piloting organizations, and not what is most profitable for non-participants.

3.5 Results

3.5.1 Baseline Results

We estimate equation 3.3 using Ordinary Least Squares (OLS); the estimates of the impact of LEED-Pilots on local registrations are reported in Table 3.2. The results are reported for 5-digit ZIP codes. Table 3.2 presents the results from estimating a pooled regression, a *difference-in-differences* (DD) model, and a *difference-in-difference-in-differences* (DDD) model. Each estimation accounts for different sources of variation to delineate the contributions of each source of variations impact on adoption.

Table 3.2: Local impact of LEED-Pilot on adoption

	Pooled	DD	DDD
LEED-Pilot Project (β)	0.0367	0.0219	0.00747
	(0.00867)	(0.00498)	(0.00303)
Observations	3,125,760	3,125,760	3,125,760
Adj. R^2	0.001	0.066	0.082
No. of Clusters	1,567	1,567	1,567

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. Clustered standard errors reported in parentheses. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models.

To measure the impact of LEED-Pilot projects on adoption of green building technology, we compare the point estimates given in Table 3.2 to the change in average LEED adoption rates in treated areas. The average change in adoption rates is calculated by comparing the average number of registrations in treated ZIP codes after a LEED-Pilot project is certified to the average number of registrations before the LEED-Pilot project is completed. For 5-digit ZIP codes, we calculate this change without accounting for within-standard variation as 0.052 and accounting for within-standard variation as 0.062.[3]

We compare the point estimates from the pooled and DD regressions to the average change in adoption rates without accounting for within-standard variation, i.e. 0.052. From the pooled estimation results, we estimate that LEED-Pilots account for 70.6% (=100% $\times$ 0.0367/0.052) of the change in adoption rates. The pooled estimate is statistically significant at the 1% level. These results, however, cannot be interpreted as causal as they can be driven by location and standard characteristics that can be confounded with the location and timing of the LEED project. Because LEED-Pilot locations where not chosen randomly, we need to account for location-specific time-invariant characteristics. After accounting for within ZIP-standard and quarterly variation in the DD estimation, we find LEED-Pilots account for 42.1% of the change in adoption rates. This implies that 28% of the change in adoption rates is statistically indistinguishable from time-invariant heterogeneity within ZIP code and standards and aggregate trends.

There is still variation in the location and timing of LEED-Pilots that can be attributed to standard-specific characteristics. Hence, in our next step, we exploit within-standard variation to control for contemporaneous shocks that raise demand for green buildings across each building standard. Exploiting this variation in the DDD estimation, we find LEED-Pilot projects account for a smaller percentage of the change in adoption rates within treated ZIP codes. Specifically, we estimate LEED-Pilot projects account for 12.0% (=100% $\times$ 0.00747/0.062) of the change in adoption rates in treated areas. The point estimate is significant at the 5% level.

Altogether, our results suggest that the LEED-Pilot program is an example of P&D projects leading to increased adoption of the technology, in this case an increase in LEED building registrations. We next present additional results to relax our identifying assump-

[3]These averages are calculated using the IHS transformed dependent variable to ensure these averages are in the same units as the coefficients in the estimated regression models.

tion, while providing initial evidence that learning drives the observed effect. We examine the role of market size and firm experience in inducing changes in adoption rates before presenting other robustness checks to illustrate the validity of our specifications and results.

Market size and firm experience

Our identification strategy relies on the assumption that no other factors affect adoption for a given standard, in a given ZIP code, at a particular time. To further test the validity of our identifying assumption, we account for two other factors that could affect adoption within a LEED standard. Specifically, we extend the DDD model in equation 3.3 to account for market size and firm experience. The new estimating equation is given by

$$\tilde{R}_{zsq} = V_{zsq} + \beta P_{zsq} + \theta M_{zsq} + \psi B_{zsq} + \varepsilon_{zsq} \tag{3.5}$$

where, as before, V_{zsq} is shorthand for the fixed effect terms and P_{zsq} is the binary treatment indicator for when a LEED-Pilot was completed. The variable M_{zsq} measures the size of the local green building market for a particular standard. We measure this as the installed-base of LEED certified buildings within a building standard. The installed-base of a technology is often used to approximate peer effects in models of technology diffusion, e.g., see Bollinger and Gillingham [114]. In our setting, the installed-base of LEED buildings may also capture the maturity of a local green building market. Because of this, we interpret the coefficient θ on the market size term as measuring the extent to which green buildings act as strategic substitutes or complements. The variable B_{zsq} measures the installed-base of certified buildings owned by firms (or organizations) that register a building in a ZIP code, standard, and quarter. In this sense, we are measuring the impact of certified buildings in other markets on local registrations. The coefficient ψ on the firm experience term measures how organizational learning affects adoption. We expect firm experience to have a positive effect on adoption, i.e. we hypothesize that $\hat{\psi} > 0$.

Table 3.3: Impact of LEED-Pilot projects, market size, and firm experience on LEED adoption

	(I)	(I)	(III)	(IV)
LEED-Pilot Project (β)	0.00747	0.00786	0.00701	0.00735
	(0.00303)	(0.00285)	(0.00304)	(0.00287)
Local Market Size (θ)		0.00550		0.00480
		(0.00186)		(0.00185)
Firm Experience (ψ)			0.00496	0.00495
			(0.000122)	(0.000120)
Observations	3,125,760	3,125,760	3,125,760	3,125,760
Adj. R^2	0.082	0.083	0.120	0.121
No. of Clusters	1,567	1,567	1,567	1,567

Notes: Reported coefficients are estimated using the DDD model. The dependent variable in each model is the IHS transformation of quarterly, privately-owned registrations. Clustered standard errors reported in parentheses and are clustered by counties. Estimated coefficients are rounded to the third significant digit for comparison across models.

Table 3.3 reports the results of estimating equation 3.5 using OLS. The results are reported in different columns to illustrate the impact of omitting market size and firm experience on the point estimate for LEED-Pilot projects. For ease of comparison, Column (I) reports the results of the baseline DDD estimate from Table 3.2.

Column (II) reports the estimates for the effect of demonstration projects and market size on green building adoption. By including market size, we find our estimate of the treatment effect $\hat{\beta} = 0.00786$ is statistically indistinguishable from the baseline model without market size, implying investment responses to LEED-Pilots are independent of market size. Yet, the point estimate does increase slightly in magnitude, and this increase suggests an underlying negative association between market size and LEED-Pilots.

We estimate an additional, certified green building in a local market contributes to a 0.55% increase in local adoption rates. This effect is significant at the 1% level. The positive, reduced-form parameter on market size $\hat{\theta} = 0.0055$ indicates green buildings may serve as strategic complements, indicating additional buildings might reduce overall investment costs in local markets. This effect could be driven by peer-to-peer interactions or general equilibrium effects, e.g. reduced input prices driven by entry of input-suppliers or specialized contractors in local markets.

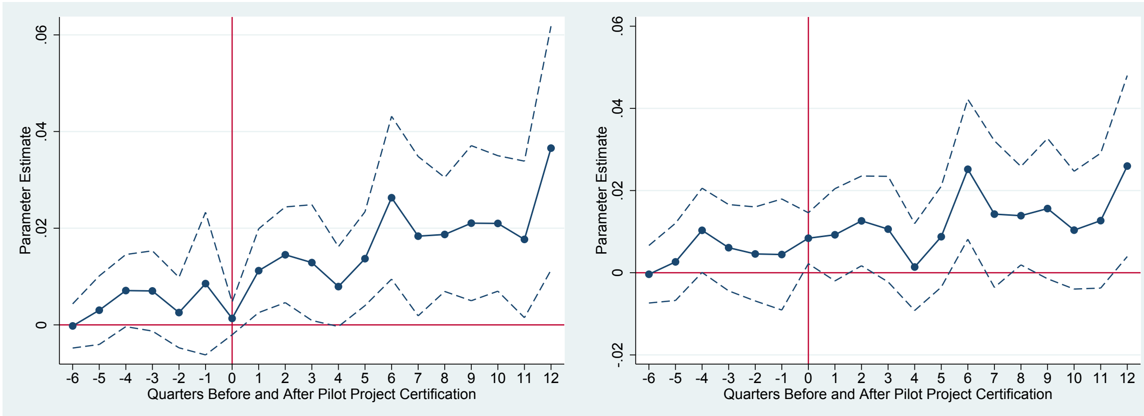
We also estimate the model including firm experience B_{zsq} in Column (III). Again, we find the estimated parameter for a LEED-Pilot project $\hat{\beta} = 0.00701$ is not changed by including additional covariates in the model. Conforming with our expectations, we find that as firms gain more experience with green building construction, local adoption rates increase. Specifically, we estimate that an additional certified building *in another ZIP code* increases local adoption rates by 0.50%. Additionally, the estimated parameter on firm experience $\hat{\psi} = 0.00496$ suggests organizational learning is an important driver of adoption.

Lastly, in Column (IV), we report the estimates including all covariates in the model. Importantly, we find the estimated effect of LEED-Pilot projects on adoption rates $\hat{\beta} = 0.00735$ is robust to the addition of both market size and firm experience in the model. The positive, statistically coefficients $\hat{\theta}$ and $\hat{\psi}$ may suggest both social and organizational learning, respectively. While consistent with our conceptualization of LEED-Pilots and other P&D programs as dual demonstration and pilot initiatives, we caution against interpretation on this evidence alone, and provide further analysis of a learning mechanism in Section 6.

3.5.2 Robustness

Parallel Trend Assumption

For the DD estimates and DDD estimates presented in Table 3.2 to be valid estimates of the causal effect of LEED-Pilot projects on adoption, the trend in adoption rates between treated and control groups must be similar before LEED-Pilot projects were introduced, conditional on observable characteristics. This parallel trend assumption ensures the control group represents a valid counterfactual baseline to evaluate the outcomes of the treatment group in the absence of a LEED-Pilot project.



(a) Difference-in-differences (b) Difference-in-difference-in-differences

Figure 3.3: Lead-lag plots for DD and DDD estimation

We evaluate the validity of this assumption in the context of our estimation framework. To do this, we estimate the following specification:

$$\tilde{R}_{zsq} = V_{zsq} + \sum_{k} \beta_k P_{zsq} + \varepsilon_{zsq} \tag{3.6}$$

In the specification above, we center the time period a LEED-Pilot is completed at $k = 0$ and evaluate the impact of LEED-Pilots from $k = -6$ quarters before and $k = 12$ quarters following this certification date. We then compare the trend across treated and control groups, before and after completion. Figure 3.3 plots the coefficients $\hat{\beta}_k$ for the DD and DDD model. The horizontal axis measures the number of quarters preceding and following the certification date of a LEED-Pilot. The vertical line centered at $k = 0$ corresponds to the normalized time period a LEED-Pilot was completed. The vertical axis is the value of the estimated parameter. The solid line corresponds to the point estimates for $\hat{\beta}_k$k and the dotted lines represent the 95% confidence intervals of these estimates.

Figure 3.3a plots the estimates from the DD model. For $k \leq 0$, the estimates are not statistically distinguishable from 0. The panel suggests that there is not a statistical difference in pre-treatment adoption trends between treated and control regions under a 95% confidence level. Further, in the step from $k = 0$ to $k = 1$, we find a statistically significant increase in adoption rates in treated regions, suggesting the completion of LEED-Pilot projects do have a positive impact on adoption decisions. Similarly, Figure 3.3b shows for the DDD model that adoption rates were not statistically different between treated and control groups in the pre-treatment period. At $k = 0$, we observe a statistically significant increase in adoption rates in the treated group, again suggesting the presence of a LEED-Pilot project increases local adoption.

3-digit ZIP code analysis

We have so far assumed the appropriate boundaries of regional real estate markets are best approximated by 5-digit ZIP codes. In this section, we test the robustness of our main results by re-defining the boundary of a regional real estate market. This robustness test also helps us to re-examine the geographic scope of spillovers from LEED-Pilots. To this end, we estimate the DDD model using 3-digit ZIP codes to approximate the boundaries of regional real estate markets. We find re-defining geographic boundaries changes the estimated impact of LEED-Pilots, in terms of the contribution of a LEED-Pilot project to the change in local adoption rates, but the overall effect is still positive and statistically significant.

Similar to the presentation of the main results in section 5.1, we compare the point estimates for the treatment effect to the change in average adoption rates when a LEED-Pilot is introduced in treated locations. After accounting for within-standard variation, the average change in adoption rates is 0.326. Column (I) presents the results from the DDD estimation using only the LEED-Pilot indicator. We estimate LEED-Pilots account for around 5% (=100% $\times$ 0.0163/0.326) of the average change in adoption rates in treated 3-digit ZIP codes.

Column (II) reports the results of the estimation when including only market size. By including market size, we find the point estimate for the treatment effect approximately doubles from the estimate presented in Column (I), again indicating a negative association

Table 3.4: Impact of LEED-Pilot projects in 3-Digit ZIP Codes

	(I)	(II)	(III)	(IV)
LEED-Pilot Project (β)	0.0163	0.0303	0.0165	0.0298
	(0.00919)	(0.00927)	(0.00905)	(0.00906)
Market Size (θ)		0.00622		0.00590
		(0.000892)		(0.000889)
Firm Experience (ψ)			0.00384	0.00382
			(0.000196)	(0.000196)
Observations	319,104	319,104	319,104	319,104
Adj. R^2	0.374	0.378	0.402	0.406
No. of Clusters	831	831	831	831

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. Clustered standard errors reported in parentheses. Standard errors for 3-Digit ZIP code estimates are clustered by 3-Digit ZIP codes. Estimated coefficients are rounded to the third significant digit for comparison across models.

between market size and P&D projects; however, the estimate is statistically indistinguishable from the estimate in Column (I) at the 5% level. We estimate market size has a positive, statistically significant impact $\hat{\theta} = 0.00622$ on adoption rates, suggesting as before that green building investments are complementary. All else constant, we find an additional certified building is expected to increase local adoption rates by 0.6%.

Column (III) reports the estimation results when including firm experience. The estimated treatment effect $\hat{\beta} = 0.0165$ is unaffected by including firm experience, and, again, we estimate firm experience $\hat{\psi} = 0.00384$ is expected to increase adoption rates. Lastly, Column (IV) reports the results of the full-specification. After including market size and firm experience, we estimate LEED-Pilot projects account for approximately 9.1% of the increase in adoption rates in treated areas. Further, the point estimates for market size and firm experience remain positive and statistically significant at the 1% level.

Continuous Treatment

The main results of this paper are presented as a step change in adoption rates because the treatment covariate is coded as a binary variable. In contrast, we can also account for trend

Table 3.5: Robustness check using the quarters after a LEED-Pilot is certified

	(I)	(II)	(III)	(IV)
Quarters After (β)	0.000636	0.000529	0.000594	0.000501
	(0.000240)	(0.000205)	(0.000236)	(0.000203)
Market Size (θ)		0.00544		0.00474
		(0.00185)		(0.00184)
Firm Experience (ψ)			0.00496	0.00495
			(0.000122)	(0.000120)
Observations	3,125,760	3,125,760	3,125,760	3,125,7604
Adj. R^2	0.082	0.083	0.120	0.121
No. of Clusters	1,567	1,567	1,567	1,567

Notes: The dependent variable is the IHS transformation of quarterly, privately-owned building registrations. The treatment variable measures the number of quarters since a pilot project received certification. All specifications are estimated using the DDD model. Clustered standard errors reported in parentheses. The average number of quarters after a pilot project receives certification is 14.34 for 5-Digit ZIP codes. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models.

changes in adoption rates using a continuous measure of treatment. In this subsection, we test for trend changes in the rate of adoption by measuring the treatment variable as the number of quarters since a completion of a LEED-Pilot. Formally, we estimate the following model

$$\tilde{R}_{zsq} = V_{zsq} + \beta \sum_{\tau \leq q} P_{zs\tau} + \theta M_{zsq} + \psi B_{zsq} + \varepsilon_{zsq} \tag{3.7}$$

The results of the estimation are reported in Table 3.5. As before, we present the results in different columns, where each column includes a different set of covariates. Further, the results are only reported for 5-digit ZIP codes. Column (I) presents the results using only the continuous measure of treatment. Subsequent columns introduce additional covariates in the model, namely market size and firm experience. Point estimates related to these covariates are nearly identical to the estimates presented in section 5.2.2; we focus our discussion of this robustness test exclusively on the treatment effect.

The estimates of the treatment effect ranges from $\hat{\beta} = 0.000501$ to $\hat{\beta} = 0.000636$, implying adoption rates increase by these magnitudes at a quarterly frequency. The average number of quarters since a completion of a LEED-Pilot is approximately 14 quarters. Evaluating the treatment effect at this average, implies the effect of LEED-Pilots projects on local adoption ranges from 0.00701 to 0.00890. Again, by comparing these point estimates to the average change in adoption rates (0.062), we find LEED-Pilot projects contribute to an additional 11-14% in adoption rates. Overall, these estimates are consistent with the 12% baseline effect from the main specification.

Alternative transformations of dependent variable

The baseline specification uses the IHS transformation of privately-owned building registrations. In this section, we test for the impact of LEED-Pilot projects using alternative transformations of the dependent variable. Table 3.6 presents the results of estimating the DDD model using different transformations of the dependent variable.

Table 3.6: Estimated impact of LEED-Pilot projects with alternative transformations

	IHS(R_{zsq})	R_{zsq}	$\ln{(R_{zsq}+1)}$
LEED-Pilot Project (β)	0.00735	0.00891	0.00573
	(0.00287)	(0.00398)	(0.00222)
Observations	3,125,760	3,125,760	3,125,760
Adj. R^2	0.121	0.1103	0.121
No. of Clusters	1,567	1,567	1,567

Notes: Clustered standard errors reported in parentheses. Standard errors for 5-Digit ZIP code estimates are clustered by county. Estimated coefficients are rounded to the third significant digit for comparison across models. Each model includes the market size and firm experience covariates.

Each estimation includes the market size M_{zsq} and firm experience B_{zsq} covariates, and the estimated coefficients for these variables are consistent with the results presented in 3.3. Hence, we only present the results for the treatment effect. We estimate two additional models using the level of privately-owned building registrations R_{zsq} and an alternative log-transformation. These estimates are presented in the second and third columns of Table 3.6, respectively. We follow the same procedure from earlier sections and compare the point estimates to the average change in adoption rates for treated markets. We calculate the average change in adoption rates as 0.080 for the level variable and 0.048 for alternative log-transformed variable.

We find the point estimates for the effect of LEED-Pilot projects on adoption using alternative transformations of privately-owned builindg registrations are consistent with the main results. Specifically, comparing the point estimates to the average change in adoption rates in treated markets, we find LEED-Pilot projects are estimated to increase adoption rates by 11.1% using the level of building registrations. Similarly, we find adoption rates increase by 12.0% using the alternative log-transformation in the third column. Overall, both results are consistent with the baseline treatment effect of 12% discussed in section 5.1.

3.6 Is adoption driven by learning or herding?

The main results presented in Table 3.2 suggest LEED-Pilots have the effect of increasing adoption of green building technologies and practices. In this sense, the results are consistent with our hypothesis that P&D projects affect local demand for green building technologies and practices. Though we show this effect is not endogenous to particular technologies, markets, or trends over time, we do not provide evidence for the mechanism driving this effect. Following the conceptual framework presented in Section 2, we investigate the possibility that observed effects are due to herding, rather than learning. The analyses that follow attempt to disentangle the mechanisms driving our main results, and collectively inform our understanding of the effectiveness of P&D programs.

Consider the possibility that the estimated increase in adoption may be driven by herding behavior rather than learning or knowledge spillovers. If observed increased uptake is due to herding, building owners may determine that P&D project stakeholders know more about the performance value of green building adoption and, consequently, imitate or conform to the actions taken by P&D stakeholders [126, 139].

In the herding model, subsequent adopters react to the presence of new certifications and mimic this behavior, regardless of the performance characteristics of the P&D project. An extreme case may result in lock-in on sub-optimal technologies, rather than the iterative improvement of practices, as would be achieved through learning. By comparison, if the project generates knowledge spillovers, impacted market players integrate new information in the decision to invest in the new technology [103], and in some cases are able to adopt at lower costs. Reductions in costs may arise from, for example, the creation of new value chains in local markets, where new social and business ties between building owners, developers, and contractors reduce transaction costs for subsequent adopters.

3.6.1 Evidence of Iterative Learning

During the deployment phase, dozens of P&D projects may be built. Nemet, Zipperer, and Kraus [2] suggests that sequentially executing P&D projects allows innovators to build from the successes and failures of previous projects, and thus improving the technology's value in each iteration. Consistent with this perspective, we assume that later LEED-Pilot projects are more refined than the earlier projects and have improved performance characteristics. Leveraging the difference between the registrations of the early versus later LEED-Pilots, we attempt to identify a learning effect that drives the subsequent uptake of LEED buildings. We use the sequential timing of LEED-Pilots to determine if adoption is driven by herding or learning about performance. If adoption is driven by herding behavior, then the value or performance characteristics of later projects should have very little impact on adoption. Herding would produce no difference between the effect of earlier versus later LEED-Pilots on adoption rates. In contrast, if adoption is driven by knowledge spillovers and learning about the performance of the technology, we should observe that later LEED-Pilots increase adoption rates more than earlier projects. In both cases, we assume that the performance of technologies and practices used in LEED-Pilots improves with each iteration. We argue that rival interpretations of trends are addressed through our DDD framework in the interpretation of these results. To test these hypotheses, we divide the LEED-Pilots into 5 bins based on the day the project registered with the USGBC. The registration date of the LEED-Pilot project corresponds to when a project registered with the USGBC and is the appropriate measure to use when trying to measure the time when a LEED-Pilot enters the program. The first bin corresponds to the first 20% of registered LEED-Pilots, with each subsequent bin representing the next quintile. We segment the bins based on percentages instead of total projects to make estimates comparable across standards that have different numbers of projects. Utilizing the empirical strategy as before, we examine differences in the trajectory of uptake of a particular LEED standard at the ZIP code level, based on the timing of the LEED-Pilots. We then estimate the following model using both the DD and DDD framework

$$\tilde{R}_{zsq} = V_{zsq} + \sum_{i=1}^{5} \beta_i P_{izsq} + \varepsilon_{zsq} \tag{3.8}$$

where the subscript i corresponds to the bins used for segmenting the timing of the LEED-Pilot projects, and P_{izsq} is a dummy variable equal to 1 if a LEED- Pilot project is in the ith bin and has registered by quarter q.

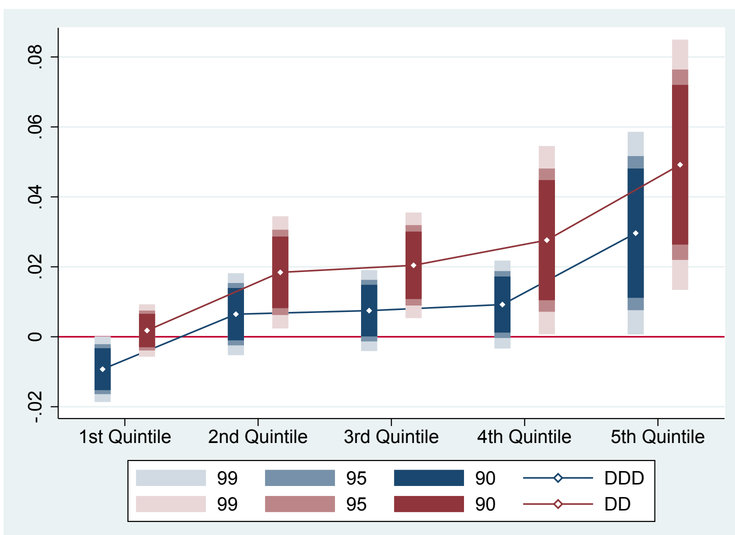


Figure 3.4: Effect of LEED-Pilot timing on adoption

Figure 3.4 presents the estimated coefficients from the model using the registration date of the LEED-Pilot projects. We present the estimated coefficients for each of the bins with their respective 90%, 95%, and 99% confidence intervals. For the purpose of comparison, we also estimate the same model using the DD framework. In both the DD and DDD estimations, there appears to be an increase in the point estimates for each iteration of LEED-Pilot projects. For the DDD estimation, we estimate that regions with the earliest registered LEED-Pilot projects experienced a statistically significant decline $\hat{\beta} = -0.00926$ in adoption rates relative to control regions, significant at the 5% level.

However, in subsequent iterations, we estimate a positive and statistically significant effect of LEED-Pilots on adoption. Notably, for the third and fourth bins, we estimate regions with these projects experienced an increase in adoption rates $\hat{\beta}_3 = 0.00748$ and $\hat{\beta}_4 = 0.00921$, both estimates being significant at the 10% level. The largest estimated impact, however, is associated with the final 20% of LEED-Pilot projects registering within a standard. We estimate these projects have the largest effect on adoption $\hat{\beta}_5 = 0.0296$, significant at the 1% level.

Although we cannot conclude that these estimates are statistically different from each other, the results of this estimation seem to suggest a process where building owners are learning about the performance characteristics of the LEED standard from LEED-Pilots. Later LEED-Pilot projects appear to have more impact on local adoption of new standards than do earlier projects. The strongest evidence in support of this conclusion comes from the estimated effects of the earliest $\hat{\beta}_1 = -0.00926$ and the latest $\hat{\beta}_5 = 0.0296$ projects. The negative point estimate for the first iteration of projects suggests these projects had little effect on resolving the technical uncertainty of LEED certification and may have actually stalled diffusion of the standard in these areas. That is, the earliest LEED-Pilot projects (which may face implementation challenges) have the smallest effect on subsequent adoption and may have inhibited future uptake of the new standard. In contrast, the large point estimate for the last quintile of projects suggests that the iterative improvements within the

LEED-Pilot program led to technical improvements to the new LEED standards. These more refined projects with improved performance characteristics increased local adoption by the largest magnitudes.

An alternative explanation for these results may be that market momentum is driving the increasing impact of LEED-Pilot projects rather than learning externalities. Recall that our DDD estimation controls for time-varying fluctuations within standards, such as changes in the prices of component technologies or general advertising and promotion of the new standard by the USGBC. To the extent market momentum is driven by these effects, the DDD estimation should control for these changes. On the other hand, momentum may vary at the regional level (i.e., at the interaction of time, technology, and location), and the estimates from the DDD model would be picking up these effects. However, this would require that the momentum behind a new standard differs substantially between treated and control regions. Because of this, we conduct additional tests to determine whether the change in adoption is driven by herding or learning externalities.

3.6.2 Evidence of Reduced Adoption Costs

In this section, we provide additional evidence supporting the claim that the change in local adoption rates following the completion of a P&D project is driven by learning rather than herding behavior. Specifically, we evaluate the impact of LEED-Pilots on the costs of achieving LEED certification to directly test this claim. If adoption is the direct result of herding behavior, and public opinion is valued more than private beliefs, then we would expect LEED-Pilots to have no effect on the costs of LEED certification. In contrast, if P&D projects increase adoption through a learning process, then we should observe a reduction in the costs of achieving LEED certification following the completion of a LEED-Pilot project.

However, because we do not directly observe the financial costs of certification, we need a suitable proxy for these costs to test our claim above. To this end, we use the number of days $\mathcal{D}$ elapsed between the day a building is registered with the USGBC and the day the building is awarded certification. Longer project completion times may proxy higher rental costs of capital equipment, labor costs of workers and contractors, as well as construction permitting costs.

Conducting this analysis requires a change in the unit of observation. Rather than evaluating the aggregate adoption rates in a geographic region, we observe a building b managed by an organization o. As before, we differentiate buildings by LEED standard s and the quarter-year q the building was registered with the USGBC. To measure project implementation time, we must limit the sample to projects that reach certification, and then calculate the number of days between registration, or intent to implement the new technology, and certification, or completed adoption. We also restrict the sample to include organizations which have at least 5 buildings that have achieved certification. Lastly, we only consider organizations that have at least 1 project before exposure to treatment. That is, if an organization does not register buildings over the "pre" period, adoption times for those organizations cannot be compared before and after the treatment. Overall, there are 329 organizations and 5,272 buildings in the restricted sample.

We estimate the following model using OLS

$$\mathcal{D}_{bosq} = \Psi_{osq} + \beta E_{osq} + \eta B_{oq} + \mathbf{X}_b^{'}\boldsymbol{\theta} + \upsilon_{bosq} \tag{3.9}$$

where $\Psi_{osq} = \zeta_o + \kappa_s + \tau_q + \omega_{os} + \rho_{sq}$ is shorthand notation for the fixed effect terms in the model. The treatment dummy E_{osq} measures whether an organization o is exposed to a LEED-Pilot by time q. We assume an organization is exposed to a LEED-Pilot project if the organization registers a building in the same 5-digit ZIP code in which a LEED-Pilot project is completed. As before, we differentiate this exposure at the level of a particular LEED standard s, meaning exposure (treatment) is defined within a standard. The treatment dummy E_{osq} is equal to 0 if an organization has not registered a building in the same 5-digit ZIP code as a LEED-Pilot and equal to 1 after a building is registered in the same 5-digit

ZIP code of a completed LEED-Pilot.

Equation 3.9 also controls for other factors that may have influenced the costs of the LEED certification process. For instance, organizational learning may have contributed to reduced certification costs if organizations are capable of utilizing previous building experience into new projects. We measure a firm's previous building experience using the installed-base B_{oq} of an organization's buildings that have achieved LEED certification. The parameter η captures the effect of this experience on the costs of achieving LEED certification. We also include building level controls $\mathbf{X}_b'$ to account for building-specific heterogeneity that may impact project delays. The vector $\mathbf{X}_b'$ includes controls for the number of credits (Points Achieved) awarded to a building based on how certification is obtained, and the building size (Square Footage) of the building. Based on the specification in equation 3.9, the main parameter of interest β corresponds to the DD estimator, similar to the estimator described in equation 3.1.[4] Table 3.7 codifies the results of the estimation. Column (I) corresponds to the estimation that only includes the treatment dummy, Column (II) includes building level controls, Column (III) includes organizational experience, and Column (IV) includes variation from all controls.

In Column (I), we estimate a negative and statistically significant effect of exposure to a LEED-Pilot project. We estimate that exposure induces an 11% reduction in the number of days required to certify a building with the USGBC. This estimate is robust to inclusion of building level controls in Column (II). We find the point estimate for exposure decreases slightly but remains negative and statistically significant at the 5% level. Further, we find the amount of technologies and practices implemented in a building, as measured by the

[4]Using the same notation as before, where o is a treated organization and o' is a control organization, the β in the equation above is similar to

$$\beta = \left(\bar{\mathcal{D}}_{os,post} - \bar{\mathcal{D}}_{os,pre}\right) - \left(\bar{\mathcal{D}}_{o's,post} - \bar{\mathcal{D}}_{o's,pre}\right) \tag{3.10}$$

Table 3.7: Effect of LEED-Pilot on Building Construction Time

	(I)	(II)	(III)	(IV)
Exposed to LEED-Pilot	-0.117	-0.0995	-0.112	-0.0942
	(0.0492)	(0.0502)	(0.0499)	(0.0504)
Points Achieved		0.00613		0.00575
		(0.00250)		(0.00232)
Square Footage (Log)		0.0526		0.0553
		(0.0208)		(0.0206)
Firm Experience			-0.00391	-0.00383
			(0.00186)	(0.00179)
No. of Observations	5,272	5,265	5,272	5,265
Adjusted R^2	0.714	0.719	0.715	0.721

Notes: Cluster-robust standard errors are reported in parentheses. Standard errors are clustered on organizations with 329 clusters. The dependent variable is the natural logarithm of project completion time. Project completion times are measured as the number of days between the registration and certification date of an individual building. The average project completion time in the sample is 596.85 days and the median completion time is 477 days. In Column (II) and (IV), 7 observations are dropped because of missing building size data.

number of credits, increases the time to achieve certification. Specifically, an additional 10 credits is associated with an increase of 6% in the certification timeframe. Lastly, we find that larger buildings require more time, on average, to achieve certification. Column (III) controls for organizational experience. We find organizational experience plays an important role in driving adoption, particularly through the cost channel. In particular, we estimate an additional certified building reduces the number of days to achieve certification by around 0.3%. Column (IV) includes all covariates in the model. We find the estimated effect of exposure to P&D projects retains its sign and is statistically significant at the 10% level.

These results suggest that LEED-Pilots reduce local costs of adoption, consistent with the expectation that demonstrations foster formation of supplier and knowledge sharing networks. This, combined with results in Section 6.1, suggest learning occurred, and the observed effect is not purely the result of herding behavior. Notably, these estimates are conservative with respect to a key assumption: that effects are highly localized. Though there is some evidence that this is true (see Section 5.2.3), organizational learning from participating in LEED-Pilots may facilitate adoption at other (non-local) establishments.

3.7 Conclusion

Pilot and demonstration (P&D) programs aim to catalyze early diffusion of new technologies. In this paper, we define pilot projects as those seeking to stoke learning within adopting firms, while demonstration projects diffuse knowledge outwards to external parties. Using data on adoption of green building technologies provided by the USGBC's LEED-Pilot program, we empirically test for the impact of P&D projects in the process of technology deployment. Using a difference-in-differences-in-differences empirical strategy that exploits quasi-experimental variation across time, geography, and certification typologies, we find that local adoption rates of the LEED green building standard increases between 5% and 12% following the completion of a LEED-Pilot project, controlling for other temporal, spatial, and industry trends.

These findings are important in understanding the promotion of beneficial technologies and market transformation. Due to a variety of market failures and barriers, the adoption of potentially effective and efficient technologies is not guaranteed. P&D projects can help lower search costs, procurement costs, and other transaction costs associated with the adoption of new technologies, as well as help promote improved understanding of the benefits and costs of new technologies. Using a quasi-experimental design, our evidence identifies an aggregate causal effect of LEED-Pilots on the adoption of innovative energy and environmental technologies. By extending this research, we are able to examine evidence of mechanisms driving these effects to deduce lessons for policy design.

We find support for several mechanisms driving the adoption of energy and environmental technologies. First, and most prominently, we find evidence for learning driving the observed increase uptake of green building strategies and technologies. This evidence comes from several sources: we find evidence for increased adoption based on past firm experience with green building technologies; we find evidence for decreased construction times if a firm has been exposed to a LEED-Pilot. Together, these findings provide strong support for learning outcomes. These findings, in addition to evidence that exposure to a LEED-Pilot project increases adoption in local markets, do not preclude the possibility that some increased uptake is due to herding behavior or mimicry. Rather, elements of our results suggest that firms differentiate successful experiments from unsuccessful ones, learning from those more effectively implemented. We find that earlier, more experimental LEED-Pilots have less impact than later, more mature, projects. Moreover, as the number of LEED-Pilot projects increases in a market, the faster the completion time is between registration and certification of a building; suggesting a mechanism in which learning spills over to non-participant developers. We also identify a within-firm learning channel, where firms with establishments exposed to LEED-Pilot projects, later implement projects in different locations, expanding the reach of LEED-Pilots beyond localized markets.

Our estimates are robust to a large number of threats to validity. The DDD estimates provide a robust causal identification strategy that controls for multiple sources of exogenous variation, including secular trends, geographic and market trends, and unobservable differences in geographic suitability for different certification vintages. Our DDD strategy addresses a challenge of identification that is persistent through much of the literature on information, technology, and policy spillovers, where adoption decisions cannot be distinctly or separately identified from other concurrent trends or influences. The finely grained data that involved individual building locations, as well as rich information about building construction date, construction duration, and certification vintages allowed for a sophisticated identification strategy and unique research context that lent itself to a robust identification strategy and a variety of research extensions that help shed light on the causal pathways for our findings.

The success of P&D programs may rely on best practices, as reflected in the LEED-

Pilot program. First, USGBC identifies and works with market leaders willing to undertake financial risks in exchange for marketing benefits. The market premium provided by being an early adopter of LEED exceeds the risks for some companies. This market premium accrues by signaling employees, customers, investors, and the community that the firm is innovative and embodies values of sustainability. The USGBC coordinates with firms engaging in LEED-Pilot projects throughout the process, essentially providing technical assistance in exchange for undertaking a risky pilot project. By pursuing numerous LEED-Pilots, the USGBC ensures the adequate development of new standards and spurs the dissemination of the new standard across industry. Together, these efforts highlight ways to incentivize the voluntary undertaking of risky P&D projects to help seed market transformation.

The LEED-Pilot program highlights a set of best practices that lead to increased uptake of energy and environmental technologies, and suggests a set of principles that can be leveraged to help disseminate the adoption of advanced technology. By providing some technical assistance and a marketing benefit in exchange for taking on a risky P&D project, USGBC encourages the early adoption of technologies and the sharing of knowledge associated with these experiments. Together, these reduce the costs for future adopters to pursue advanced energy and environmental technologies by promoting learning about the costs and benefits of emergent technologies and reducing the costs associated with procuring and implementing new energy and environmental technologies. Moreover, the USGBC may be able to strategically select or recruit early adopters, favoring those with high market status or visibility, in order to facilitate the broadest impact on subsequent adoption. In a world where the rapid diffusion of advanced technologies may be vital to reducing environmental impact, this study highlights the potential role of information programs in spurring investment that can promote broader market transformation.

CHAPTER 4

ENERGY EFFICIENCY AND PRODUCTION NETWORKS

Industrial activity periodically undergoes breakthrough innovations in energy efficiency. However, the structure and complexity of industrial supply chain networks can significantly impact the realized aggregate benefits of such innovations. I show the existence of a supply chain network creates a channel through which micro-scale energy efficiency improvements generate aggregate energy savings, which I refer to as an *energy savings multiplier*. This multiplier effect arises only under specific network configurations in which producers source intermediate inputs through direct and indirect upstream supply chains. My main results show aggregate energy savings are largely determined by these indirect interconnections, and highlight how similar energy efficiency improvements can result in drastically different aggregate energy savings outcomes. As production processes are becoming increasingly dependent on globalized supply chain networks, my findings have important implications for designing and managing industrial energy efficiency policy in an interconnected world.

4.1 Introduction

Economic growth is fueled by access to more productive energy resources. Earlier periods of growth were driven by the discovery and use of previously unavailable energy resources. Within the past century, however, continued economic growth can be partially attributed to the more productive use of scarce energy resources. The proliferation of more efficient energy service technologies, such as heating, lighting, and transport technologies, have led to reductions in global energy intensiveness, but these reductions are far smaller than anticipated. Since the late 19th century, global energy intensiveness has declined by only 62 percent, despite a twofold increase in the efficiency of energy service technologies.

Moreover, this observed asymmetry appears to have widened throughout the past century.

In this paper, I argue the widening gap between micro-scale efficiency gains and reductions in global energy intensiveness may be driven by a global shift in the nature of industrial activity. Production of many goods and services now require a broader range of inputs than in the past. Over the past century, this feature of production is engendered by the increased organization of industrial activity into complex, global supply chain networks. These production networks reflect the intricate web of connectivity between firms and sectors in the economy. The structure of these interconnections has important implications for how energy efficiency shocks transmit throughout the economy, and may explain why the magnitude of micro-scale energy efficiency improvements may not be reflected at the aggregate level.

I propose a model that embeds energy efficiency within a production network to study how micro-scale, industrial energy efficiency improvements translate into aggregate economic outcomes. I model energy efficiency improvements as an increase in the capacity of a sector to transform primary energy resources into useful energy services. Producers combine energy services with other intermediate inputs to produce output, and this output is then distributed as an intermediate input to other sectors or as a final good for consumption. Production networks collect all the intermediate input transactions between producers in the economy. In a production network, two sectors will be connected if there is intermediate input trade between them. The strength of the connection between them is determined by the importance of the other sector's intermediate in their own production process. In the model, I assume that energy efficiency improvements alter the input relationships between the energy sector and the other sectors in the economy. Producers adjust to this new input relationship by re-allocating the inputs used in their production process. The extent of their adjustment depends, not only on how their suppliers respond to the efficiency shock, but also how their suppliers' suppliers respond to it. Thus, the overall response to an efficiency improvement and the resulting aggregate energy savings are determined by the structure of the production network.

Using this framework, I find the direct and indirect input transactions between sectors in the economy's production network determines the magnitude of aggregate energy savings. Specifically, I show the existence and nature of input linkages within the production network creates a new pathway for aggregate energy savings from industrial energy efficiency improvements, an *energy savings multiplier*. For sectors with similar observable attributes, such as energy intensiveness or the elasticity of substitution between inputs, heterogeneity in upstream and downstream supply chains translate into different factor and commodity market adjustments following the efficiency improvement. Price adjustments in these markets cause producers to re-allocate the inputs used in their production process, leading to potentially drastic differences in aggregate energy savings arising from the same energy efficiency improvement.

I demonstrate how the production network shapes factor and commodity market adjustments by decomposing aggregate energy savings into three channels—a price channel, a growth channel, and a composition channel. First, I show economy-wide energy savings from the price channel can be positive or negative depending on the nature of price adjustments in energy and factor markets. If factor prices rise to a sufficiently high level, energy production becomes more costly, and the quantity of energy produced in the economy declines. Second, I show the energy service efficiency improvement spurs growth in the economy, raising household income. I find that aggregate energy consumption increases through this growth channel when households spend this additional income on goods or services that directly or indirect rely on energy as an input to production. Third, I show efficiency improvements alter the embodied energy requirements of goods and services produced in the economy through a composition channel. As product supply chains become more or less energy-intensive, the structural importance of the energy sector adjusts, leading to a change in aggregate energy consumption.

For each channel, I show that re-allocation within energy supply and distribution chains creates a multiplier effect for energy savings. Formally, I decompose each channel into a direct and network-driven component. The direct component of energy savings corresponds to the change in energy production in the absence of intermediate input trade between non-energy sectors in the economy. The network-driven component of energy savings captures the impact of re-allocation of inputs within intermediate supply chains on total energy savings. To quantify the relative contribution of network-driven energy savings to overall energy savings, I introduce the *energy savings multiplier* (ESM). The ESM captures the additional energy savings or losses generated by re-allocation of energy resources within the economy's production network. In a less formal sense, the ESM compares aggregate energy savings in a world with production networks to what aggregate energy savings would be in a world without production networks. I show the measure is derived from the theoretical model and is independent of the energy-intensity of the sector experiencing the efficiency improvement. This feature of the ESM makes the measure ideal for delineating the impact of production networks on overall energy savings.

To complement the theoretical contributions of the paper, I conduct a simulation exercise using detailed state-level, input-output tables. Specifically, I calibrate the economic model for each U.S. state, introduce a 10% energy efficiency improvement to energy-intensive sectors, and compute the ESM for each efficiency shock. The results of the simulation show heterogeneity in energy supply and distribution chains can lead to drastically different results for the same efficiency shock. For some states, the ESM exceeds unity, implying supply chain re-allocation amplifies the original efficiency improvement. For other states and sectors, the ESM is less than unity, suggesting re-allocation in supply chains reduces total energy savings. I connect the magnitude of the ESM with a well-known network centrality concept to show heterogeneity across production networks drives the heterogeneity in outcomes of energy efficiency improvements.

Energy efficiency improvements can improve the productivity of fossil fuel resources while simultaneously reducing the environmental impact of their usage. However, the net benefits of energy efficiency improvements are not easily identified a priori and have been a subject of interest among resource and environmental economists for more than a century. The earliest insight on the subject is generally attributed to Jevons [140], who observed that potential energy savings from energy efficiency improvements may be partially offset by behavioral responses to changing market conditions. Since this early contribution, numerous studies have sought to identify the meaningful economic drivers that affect aggregate energy consumption following energy efficiency improvements.

Prior studies tend to focus on the partial equilibrium responses to energy efficiency improvements [141, 142]. However, in a variety of more general settings, a singular focus on partial equilibrium channels is inadequate for pinning down the net benefits of energy efficiency increases. For example, when evaluating the efficacy of large-scale, industrial energy efficiency improvements, partial equilibrium methods should be deployed with caution because these methods ignore how additional adjustments in commodity and factor prices might affect aggregate energy consumption. By accounting for interactions between commodity and factor markets in general equilibrium, many studies recognize that economy-wide market adjustments may substantially alter aggregate energy savings [143, 144]. However, less attention has been given to how the structure of industrial activity affects the transmission of energy efficiency shocks throughout the economy, shapes the nature of adjustments in commodity and factor markets, and ultimately determines aggregate energy savings.

The key insight delivered by this study is that general equilibrium energy savings are either amplified or curtailed depending on the structure of the economy's production network. Improving on recent contributions, I connect previously identified general equilibrium channels for energy savings with production networks to show industrial supply and distribution chains determine the magnitude of these channels. Böhringer and Rivers [145] show aggregate energy savings emerge from a composition effect, a growth effect, a price effect, and a labor supply effect. Lemoine [146], in contrast, focuses only on the composition channel. I advance this literature by showing the composition, growth, and price channels are the consequence of re-allocation within upstream and downstream supply chains throughout the economy. Consequently, I am able to emphasize the role of the economy's production network for mapping adjustments in commodity and factor markets following an efficiency shock to aggregate energy savings.

The main contributions of this paper are closely aligned with the tradition of theoretical general equilibrium models of economy-wide energy savings. Early contributions in this area only consider single-sector models and emphasize the growth effects created by energy efficiency improvements [147, 148, 149]. Recent contributions, however, relax the single-sector assumption and extend the analysis to a static, multi-sector framework and identify additional drivers of general equilibrium savings [145, 146, 150]. Although they account for inter-sectoral impacts from energy efficiency improvements in a multi-sector framework, these studies do not explicitly consider supply chain relationships between sectors in the economy. Notably, the input-output relationships between sectors are commonly used in numerical assessments of economy-wide energy savings. For instance, input-output tables are used to calibrate computable general equilibrium models [151, 152, 153, 154] and to calculate the multipliers in demand-driven input-output analysis of energy efficiency improvements [155, 156, 157]. In this paper, I introduce a multi-sector theoretical framework of general equilibrium energy savings that accounts for these input-output relationships. Consequently, I bring the tradition of theoretical general equilibrium models and numerical assessments of economy-wide energy savings to closer alignment.

The idea that input-output relationships affect the transmission of economic shocks dates back to the seminal contribution of Leontief [157] and Hirschman [158]. On the theoretical side, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi [159] study whether idiosyncratic sectoral productivity shocks can meaningfully impact aggregate output in the economy. They find that, in the presence of input-output linkages, the propagation of sectoral productivity shocks may drive output volatility if significant asymmetries exist between supply chains in the economy. However, the Cobb-Douglas, perfectly competitive framework constrains shocks to only transmit to downstream industries and do not stimulate upstream adjustments. Recognizing this limitation, Baqaee [160] extends the analysis to a Dixit and Stiglitz [161] monopolistic competition framework. He shows adjustments along the extensive margin, catalyzed by endogenous entry and exit of firms, cause adjustments in both upstream and downstream industries. The model in this paper most closely resembles the constant elasticity of substitution (CES) setup of Baqaee [160] but with perfect competition. Further, I depart from these studies by considering exogenous technological progress, as represented by variations in the economy's production network [162, 163, 164], as the locus of change. By doing so, I show efficiency improvements can translate into both upstream and downstream adjustments even in a perfectly competitive framework.

The organization of the paper is as follows. Section 4.2 introduces the economic environment and conveys the results for the first order conditions. In this section, I sketch out the basic economic framework that guides the rest of the paper. In Section 4.3, I introduce general equilibrium in the model, and I show two well-known centrality concepts directly map to equilibrium prices and output levels in the economy. Section 4.4 provides a discussion on how shocks propagate in the model and provides an important proposition for characterizing this propagation process. Section 4.5 provides formal, closed-form characterizations of economy-wide energy savings. Moreover, I decompose aggregate energy savings into different channels and provide interpretations of the results. Following the decomposition, I take the model to the data and simulate energy efficiency improvements in Section 4.6. Lastly, Section 4.7 concludes the paper.

4.2 The Model

I consider a static model with two types of agents, a representative consumer and industrial producers. The representative consumer is assumed to maximize utility over an exogenous, discrete set of consumption goods and services. This consumption set is divided into an energy commodity c_e and $N-1$ non-energy commodities c_i. The representative consumer inelastically supplies a fixed labor endowment of $\bar{L}$ and collects income $C = w\bar{L}$, where w is the economy-wide wage rate.

Each producer in the model corresponds to a sector. Producers are assumed to choose input bundles to minimize the total cost of a given level of production. Producers in the N sectors allocate goods and services for both intermediate use in other sectors and final-use consumption by the representative household. I assume markets for goods and services are perfectly competitive, and each sector production technology uses labor supplied by the representative consumer and intermediate inputs sourced from other sectors in the economy.

4.2.1 Preferences

The representative consumer's preferences are modeled using a constant-elasticity of substitution (CES) utility function U defined over $i \in \{e, 2, \ldots, N\}$ industrial products. In the remainder of the paper, I modify the index of products such that the energy commodity e is in the first index. The representative consumer chooses consumption levels c_i according to the following program

$$\begin{aligned} \max_{\{c_e, c_2, \ldots, c_N\}} U(c_e, c_2, \ldots, c_N) &= \left[\alpha_e^{\frac{1}{\sigma}} c_e^{\frac{\sigma-1}{\sigma}} + \sum_{i \neq e}^{N-1} \alpha_i^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\ \text{s.t.} \quad C &= p_e c_e + \sum_{i \neq e}^{N-1} p_i c_i \end{aligned} \tag{4.1}$$

where $\sigma > 0$ is the household's elasticity of substitution, the parameters $\alpha_i \geq 0$ $\forall i \in \{e, 2, \ldots, N\}$ capture the representative consumer's tastes for goods and services produced in the economy, p_i is the price of sector i's product, and C is the income of the consumer.

First-order conditions

I choose the consumer price index, which measures the cost of purchasing one unit of utility, as the numeraire of the economy so that all prices are expressed in real terms. The consumer price index P_h is given by

$$P_h = \left(\alpha_e p_e^{1-\sigma} + \sum_{i \neq e}^{N-1} \alpha_i p_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = 1 \tag{4.2}$$

Consumers choose a consumption plan $\mathbf{c}$ to maximize utility U according to the constrained maximization problem in (4.1). The maximization routine takes the economy-wide wage rate w, exogenous taste parameters α, and labor endowment $\bar{L}$ as given. In equilibrium, household demand for goods and services is determined by consumer preferences, product prices, and household income. The first-order conditions from the consumer's maximization problem imply household demand for good i is expressed as

$$c_i = \alpha_i p_i^{-\sigma} C \tag{4.3}$$

Equation (4.3) implies household demand for good i will increase when product prices decline and household incomes rise. These standard results will be useful when interpreting the price and growth channels of aggregate energy savings.

4.2.2 Production

Producers in the economy utilize a constant returns-to-scale CES production technology to produce goods or services. Each sector i (the purchasing sector) combines intermediate inputs x_{ji} from other industries j (the supplying sector) with labor L_i provided by the representative consumer. Sector i's production technology is characterized as

$$y_i = \left[\gamma_i^{\frac{1}{\sigma}} L_i^{\frac{\sigma-1}{\sigma}} + \omega_{ei}^{\frac{1}{\sigma}} \left(\phi_{ei} x_{ei} \right)^{\frac{\sigma-1}{\sigma}} + \sum_{j \neq e}^{N-1} \omega_{ji}^{\frac{1}{\sigma}} x_{ji}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{4.4}$$

I assume each sector combines a raw energy input x_{ei} with an energy conversion technology ϕ_{ei} to produce an energy-service. The parameter ϕ_{ei} directly measures the productivity of a sector's energy conversion technology and variations in this parameter are the source of energy efficiency improvements in the model. Let $\boldsymbol{\phi}$ be an $N \times N$ matrix of these productivity parameters. By construction, the first row corresponds to the energy productivity parameters of each sector and the remainder of entries in the matrix are equal to 1.[1]

The parameters ω_{ei} and ω_{ji} for $i \in \{e, 2, \ldots, N\}$ are the technical (input-output) coefficients of sector i and are exogenously determined. I normalize the coefficients in the production function for simplicity. Collectively, these coefficients define the structure of the intermediate production network of the economy [159, 160]. The input-output network of the economy is represented by the $N \times N$ matrix $\boldsymbol{\Omega}$ of these input-output coefficients.[2] Lastly, the parameter γ_i is a distribution parameter measuring the labor intensiveness of sector i.

I assume that firms in each industry minimize the costs of production subject to the available production technology given in equation (4.4). Given exogenous labor share parameter γ_i and the input-output coefficients ω_{ji}, firms in sector i choose labor L_i and intermediate inputs $\{x_{ei}, x_{2i}, \ldots, x_{Ni}\}$ to solve the following minimization problem

$$\begin{aligned} \min_{L_i, \{x_{ei}, x_{2i}, \ldots, x_{Ni}\}} & wL_i + p_e x_{ei} + \sum_{j \neq e}^{N-1} p_j x_{ji} \\ \text{s.t.} \quad & y_i^{\frac{\sigma-1}{\sigma}} = \gamma_i^{\frac{1}{\sigma}} L_i^{\frac{\sigma-1}{\sigma}} + \omega_{ei}^{\frac{1}{\sigma}} \left(\phi_{ei} x_{ei}\right)^{\frac{\sigma-1}{\sigma}} + \sum_{j \neq e}^{N-1} \omega_{ji}^{\frac{1}{\sigma}} x_{ji}^{\frac{\sigma-1}{\sigma}} \end{aligned} \tag{4.5}$$

where w is the economy's wage rate and p_i is the market price for sector i's output.

[1] This can be extended to any other technological improvement in the economy that reduces the direct requirements between industries.

[2] This is also sometimes referred to as the direct requirements matrix.

First-order conditions

Producer's choose labor inputs L_i and intermediate demand x_{ji} to minimize total production costs given the production technology in equation (4.4), exogenous energy conversion productivity parameters ϕ_{ei}, and the exogenous input-output network $\mathbf{\Omega}$. After solving the producer's minimization problem, sector i's demand for energy and non-energy intermediates are given by the expressions

$$x_{ei} = \left(\frac{\omega_{ei}}{\phi_{ei}}\right)\left(\frac{p_{si}}{\mu_i}\right)^{-\sigma} y_i \tag{4.6a}$$

$$x_{ji} = \omega_{ji}\left(\frac{p_j}{\mu_i}\right)^{-\sigma} y_i \tag{4.6b}$$

Sector i's demand for energy x_{ei} depends on several quantities of interest. First, intermediate demand for energy will be proportional to sector i's energy intensiveness. Second, demand for energy inputs will depend on the price of energy services $p_{si} = {}^{p_e}\!/\!{}_{\phi_{ei}}$ and the marginal cost of a production μ_i. Third, intermediate demand for energy will vary with production levels y_i.

4.3 Equilibrium Prices and Quantities

In this section, I relate equilibrium prices $\mathbf{P}$ and production levels $\mathbf{y}$ to two well-known network centrality concepts. Notably, the production technology in equation (4.4) permits derivation of closed-form analytical solutions to the economic environment introduced in Section 4.2. Using Definition 1, I illustrate how equilibrium prices in the economy are determined by a sector's *consumer centrality*. Taking this a step further, I show that sector output levels are determined by a combination of *consumer* and *supplier centrality*.

4.3.1 Equilibrium

An equilibrium of the model is met when household's maximize utility subject to their income constraint, producers minimize costs within a perfectly competitive environment, and commodity and factor prices clear the markets. Formally,

definition

Definition 1 ***(General Equilibrium)*** *A general equilibrium in this economy* $\mathcal{E} = (\mathbf{P}, w, \mathbf{X}, \mathbf{y}, \mathbf{c}, \boldsymbol{L})$ *is characterized by an* $N \times 1$ *vector of output prices* $\mathbf{P}$*, an economy-wide wage rate* w*, an* $N \times N$ *matrix of intermediate demand* $\mathbf{X}$*, an* $N \times 1$ *vector of total output* $\mathbf{y}$*, an* $N \times 1$ *final-use consumption plan* $\mathbf{c}$*, and an* $N \times 1$ *vector of labor demand* $\mathbf{L}$*, such that the following conditions are met:*

1. *Given the exogenously determined* $N \times 1$ *vector of taste parameters* $\boldsymbol{\alpha}$*, the consumption plan* $\mathbf{c}$ *maximizes utility* U *subject to the consumer's budget constraint* $C = w\bar{L}$
2. *The production plan given by the vector of total output* $\mathbf{y}$*, the matrix of intermediate demand* $\mathbf{X}$*, and the vector of labor demand* $\mathbf{L}$ *minimize the total costs of production for each sector and are technologically feasible given exogenously determined productivity parameters* $\boldsymbol{\phi}$*, the input-output network* $\boldsymbol{\Omega}$*, and labor intensities* $\boldsymbol{\gamma}$
3. *Markets for each good and the labor market clear. In other words, the conditions* $\mathbf{y} = \mathbf{X}\boldsymbol{\iota} + \mathbf{c}$ *and* $\bar{L} = \mathbf{L}\boldsymbol{\iota}$*, where* $\boldsymbol{\iota}$ *is an* $N \times 1$ *vector of ones, must be satisfied.*

4.3.2 Equilibrium Prices

In this section, I connect the price adjustment process to underlying changes in intermediate and factor input costs and relate equilibrium market prices to the economy's production network. Under perfect competition, firms in each sector will price their output at their marginal cost of production. Assuming firms operate in perfectly competitive markets, a firm's output price is given by

$$p_i = \mu_i = \left(\gamma_i w^{1-\sigma} + \omega_{ei} p_{si}^{1-\sigma} + \sum_{j \neq e}^{N-1} \omega_{ji} p_j^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{4.7}$$

Equation (4.7) shows the market price for a sector's product is determined by other factor and commodity prices in the economy. The direct relationship between market prices is governed by the columns of the input-output matrix $\mathbf{\Omega}$ of the economy.

Before characterizing equilibrium prices, I introduce the following proposition that allows for technological changes in the economy to be expressed as changes in the direct requirements of physical units of input

Proposition 1 ***(Productivity-Adjusted Input-Output Network)*** *The productivity-adjusted input-output network relates the production technologies given in (4.4) to physical inputs and thus variations in the intensity of input usage are expressed as changes in physical units. The productivity-adjusted input-output coefficient for energy inputs is given by*

$$\omega_{ei}^* = \phi_{ei}^{\sigma-1} \omega_{ei} \tag{4.8}$$

and the productivity-adjusted input-output network is given by $\mathbf{\Omega}^* = \boldsymbol{\phi}^{\sigma-1} \odot \mathbf{\Omega}$*, where the exponent represents is element-wise exponentiation and the character* $\odot$ *is the Hadamard product. An expression for the input-output coefficient can be derived by re-arranging equation (4.6a). Formally, I find the exogenous input-output coefficient for energy* ω_{ei} *is expressed in energy-service units. That is,*

$$\begin{aligned} \omega_{ei} &= \phi_{ei}^{1-\sigma} \frac{p_e^\sigma x_{ei}}{p_i^\sigma y_i} \\ &= \frac{p_{si}^\sigma s_{ei}}{p_i^\sigma y_i} \end{aligned}$$

where s_{ei} *is the energy-service and* p_{si} *is the energy-service price. By multiplying* ω_{ei} *by*

$\phi_{ei}^{\sigma-1}$*, I adjust the input-output coefficient by the productivity of the conversion technology. This implies the adjusted input-output coefficient is expressed as ratios of physical units. In other words,*

$$\omega_{ei}^* = \phi_{ei}^{\sigma-1}\omega_{ei} = \frac{p_e^\sigma x_{ei}}{p_i^\sigma y_i}$$

For the remainder of the paper, I will use $\mathbf{\Omega}^*$ to denote the *productivity-adjusted* input-output matrix and make the following assumption regarding the entries in the matrix

Assumption 1 *The productivity of a sector's energy conversion technology ϕ is sufficiently small so that the entries of $\mathbf{\Omega}^*$ satisfy $|\omega_{ij}^*| < 1$,$\forall ij$*

Assumption 1 is innocuous in the context of energy efficiency. In this case, I can scale the units of the energy conversion technology to ensure ϕ_{ei} is sufficiently small for all sectors. The assumption is necessary for convergence.

The system of output prices given in equation (4.7) can be written as

$$\mathbf{P}^{1-\sigma} = \boldsymbol{\gamma} w^{1-\sigma} + \mathbf{\Omega}^{*'}\mathbf{P}^{1-\sigma} \tag{4.9}$$

The appearance of the term $\mathbf{\Omega}^{*'}$ in equation(4.7) captures the idea that technological improvements leads to structural changes in the economy's production network, and these changes will translate into fluctuations in commodity prices.

The following definition provides the foundation for connecting commodity prices with the structure of the economy's production network.

definition

Definition 2 ***(Multiplier Matrix)*** *Given Assumption 1 holds, then the multiplier matrix* $\mathbf{M}$ *is an $N \times N$ matrix given by*

$$\mathbf{M} = [\mathbf{I} - \mathbf{\Omega}^*]^{-1} \tag{4.10}$$

and is non-singular.

The multiplier matrix $\mathbf{M}$ has a similar interpretation to the Leontief inverse matrix in input-output analysis [157, 165]. The multiplier matrix accounts for direct and indirect interactions between sectors in the economy.

Solving equation (4.9) for $\mathbf{P}$ and using Definition 2, equilibrium commodity prices are represented as

$$\mathbf{P} = \left(\mathbf{M}'\boldsymbol{\gamma}\right)^{\frac{1}{1-\sigma}} w \tag{4.11}$$

The term $\mathbf{M}'\boldsymbol{\gamma}$ is an $N \times 1$ vector of Bonacich [166] centralities of each sector. Larger centrality values imply a sector occupies a more "central" position in the economy's production network as a purchaser of intermediate inputs and factors of production. In heterogeneous production networks, some sectors may be more susceptible to price shocks because of their more central role as a purchaser in the economy. In traditional input-output analysis, the systemic importance of a particular sector as purchaser of intermediate and factor inputs is captured by the *consumer centrality* indicator [160]. In my model, I define the *consumer centrality* indicator as:

definition

Definition 3 ***(Consumer Centrality)*** *The vector of consumer centralities is defined as*

$$\boldsymbol{\Delta} = \mathbf{M}'\boldsymbol{\gamma} \tag{4.12}$$

The consumer centrality of a sector measures the systemic importance of a sector as a direct or indirect purchaser of intermediate and factor inputs in the economy.

Combining Definition 3 with the expression for prices in equation (4.11) yields closed-form solutions for energy and non-energy commodity prices, respectively

$$p_e = \boldsymbol{\Delta}_e^{\frac{1}{1-\sigma}} w \tag{4.13a}$$

$$p_i = \boldsymbol{\Delta}_i^{\frac{1}{1-\sigma}} w \tag{4.13b}$$

The expression for prices in (4.13a) and (4.13b) illustrates the relationship between equilibrium prices and intermediate supply chains. Specifically, the model predicts that consumer centrality play an important role in determining prices in equilibrium, and this relationship depends on the elasticity of substitution in the economy. When production processes approach the Leontief limit ($\sigma \to 0$), the expression predicts that prices will be higher in sectors with higher consumer centrality.

The intuition underlying this prediction follows from the theory of cost pass-through ([167]). In vertical supply chains, an upstream producer's prices are a downstream producer's costs, and price shocks in upstream markets will propagate throughout the supply chain only to the extent these price variations are passed on to downstream industries in the supply chain. The rate at which these price variations are passed through to downstream buyers is proportional to the price elasticity of demand for the upstream producer's products. When there is less scope for substitution, then sectors with a more central role as intermediate and factor input purchasers will be more exposed to the price shock than less central sectors.

4.3.3 Equilibrium Output

Combining the market clearing condition for goods and services, $\mathbf{y} = \mathbf{X}\boldsymbol{\iota} + \mathbf{c}$, with the results from (4.3), (4.6a), (4.6b), and (4.7) yields the following system of equations

$$(\mathbf{P}^{\sigma} \odot \mathbf{y}) = \boldsymbol{\alpha} C + \boldsymbol{\Omega}^{*} (\mathbf{P}^{\sigma} \odot \mathbf{y}) \tag{4.14}$$

where the exponents on the matrices represent element-wise exponentiation and $\mathbf{y}$ is an $N \times 1$ vector of total output. Solving this equation for $(\mathbf{P}^{\sigma} \odot \mathbf{y})$ yields the equilibrium sales vector. Formally, the equilibrium sales vector is expressed as

$$
\begin{aligned}
(\mathbf{P}^{\sigma} \odot \mathbf{y}) &= [\mathbf{I} - \mathbf{\Omega}^{*}]^{-1} \boldsymbol{\alpha} C \\
&= \mathbf{M} \boldsymbol{\alpha} C
\end{aligned} \tag{4.15}
$$

Similar to equation (4.11), the entries in the vector $\mathbf{M}\boldsymbol{\alpha}$ correspond to Bonacich [166] centralities. These centralities capture a sector's direct and indirect role as a supplier of final goods to the household. Larger values suggest these sectors are influential in the supply of intermediate inputs in the economy. While the consumer centrality indicator measures the systemic influence of a sector as a purchaser in the economy, the *supplier centrality* indicator measures the systemic influence of a sector as a supplier of intermediate goods and services [160]. I define the supplier centrality indicator in the model as follows:

definition

Definition 4 ***(Supplier Centrality)*** *The vector of supplier centralities is defined as*

$$
\boldsymbol{\Upsilon} = \mathbf{M} \boldsymbol{\alpha} \tag{4.16}
$$

The supplier centrality of a sector measures the systemic importance of a sector as a direct or indirect supplier of intermediate goods in the economy.

To solve for total production in the energy and non-energy sectors, I substitute the expressions household demand (4.3), intermediate demand for energy (4.6a) and non-energy (4.6b) commodities, and the sales vector in (4.15) into the market clearing condition. Equilibrium production in the energy and non-energy sectors, respectively, is characterized as

$$y_e = c_e + \sum_j x_{ej} = \alpha_e p_e^{-\sigma} C + \sum_j \omega_{ej}^* p_e^{-\sigma} \Upsilon_j C \tag{4.17a}$$

$$y_i = c_i + \sum_j x_{ij} = \alpha_i p_i^{-\sigma} C + \sum_j \omega_{ij} p_i^{-\sigma} \Upsilon_j C \tag{4.17b}$$

The expressions for equilibrium output in (4.17a) and (4.17b) contain three useful for predictions evaluating how energy efficiency shocks generate aggregate energy savings. First, the model predicts how higher output prices reduce sector output levels in equilibrium. The intuition for this result is straightforward and follows from the law of demand, where higher output prices reduce the quantity demanded for a sector's product. The second prediction of the expression for equilibrium output levels implies production levels in the economy are positively related with the income-level in the economy. Because there is no saving in the model, consumer exhaust their income on purchasing goods and services in the economy. When incomes increase, consumer will increase demand for final goods and services. The final prediction relates to a sector's upstream position in the economy's production network. If a sector is more essential for supplying final goods to the household, i.e. has a higher supplier centrality, the model predicts production will be higher in this sector.

4.3.4 Equilibrium Wages

Applying Shephard's lemma to the expression for prices in (4.7) implies the conditional demand for labor is given as

$$L_i = \gamma_i w^{-\sigma} p_i^{\sigma} y_i \tag{4.18}$$

Equilibrium wage rates in the economy are solved for by combining the expression for labor demand with the full employment condition $\bar{L} = \sum_i L_i$ and (4.15). The economy's equilibrium wage rate is given by

$$w = \frac{C}{\bar{L}} = \left(\boldsymbol{\Upsilon}'\boldsymbol{\gamma}\right)^{\frac{1}{\sigma-1}} \tag{4.19}$$

The expression above implies that equilibrium wage rate is determined by the distribution of supplier centrality in the economy.[3] When labor-intensive sectors occupy a more central position as a supplier of intermediate goods in the economy, the expression predicts wage rates will be higher. In this sense, the expression in (4.19) can be viewed as a network-adjusted labor-intensiveness of the economy. As illustrated in Section 4, when energy efficiency shocks induce structural changes in the economy's production network, the distribution of supplier centrality will adjust and affect the overall labor-intensiveness of the economy, increasing the equilibrium wage rate. I show this effect creates a tension between the price and growth channels of aggregate energy savings.

4.4 Propagation

Structural changes in the production network affect optimal energy savings both directly and indirectly. The indirect effects come from the re-allocation of resources in upstream and downstream industries in the energy supply chain. This re-allocation process can be explicitly studied through changes in the multiplier matrix $\mathbf{M}$ following an efficiency shock. In the input-output analysis literature, the structural path analysis (SPA) methodology of Defourny and Thorbecke [168] has been widely-deployed to study the transmission of shocks throughout the economy's production network. In this section, I show the methodology can be applied to study the transmission of energy efficiency shocks in a general equilibrium setting.

[3] Alternatively, wages can also be expressed as a function of consumer centralities. In particular, the economy's wage rate can be written as

$$w = \left(\boldsymbol{\alpha}'\boldsymbol{\Delta}\right)^{\frac{1}{\sigma-1}}$$

The following definition will be useful for studying the transmission of efficiency shocks through the economy's production network.

Definition 5 ***(Power Series Expansion)*** *Given Assumption 1 holds, the power series expansion of the productivity-adjusted input-output matrix is defined as*

$$\mathbf{M} = \sum_{k=0}^{\infty} \left(\boldsymbol{\phi}^{\sigma-1} \odot \boldsymbol{\Omega}\right)^k = \sum_{k=0}^{\infty} \boldsymbol{\Omega}^{*k} \tag{4.20}$$

where the exponent k represents a matrix power.

Definition 5 decomposes the multiplier matrix into the contributions made by the underlying supply chains of the economy. The concept is similar to counting the number of walks between two nodes in a network [169, 170] in that the i, j-th entry in $\boldsymbol{\Omega}^{*k}$ measures the contribution of supply chains of length k connecting the two sectors to sector i's multiplier. For instance, holding all else constant, consider a stimulus of dC to household income. Households will spend a fraction of the stimulus $\alpha_j dC$ on purchasing products from sector j. Consequently, sector j's will expand production to meet the increased final goods demand. To produce more output, sector j will need to source more intermediate inputs from it's direct suppliers. These direct suppliers will, however, require more intermediate inputs from their direct suppliers, and so forth. This cascading process is captured by the orders of the input-output matrix $\boldsymbol{\Omega}^{*k}$. Generally, supply chains of length k connecting i to j would contribute an increase of $\boldsymbol{\Omega}^{*k}_{ij}\alpha_j dC$ to sector i's overall change in output from a dC stimulus to household income.

I represent energy efficiency improvements as technological shocks to the economy. In the model, efficiency improvements manifest as changes in the input-output architecture of the economy. These changes then transmit through the economy's multiplier matrix. The change in the multiplier matrix with respect to a 1% energy efficiency improvement in

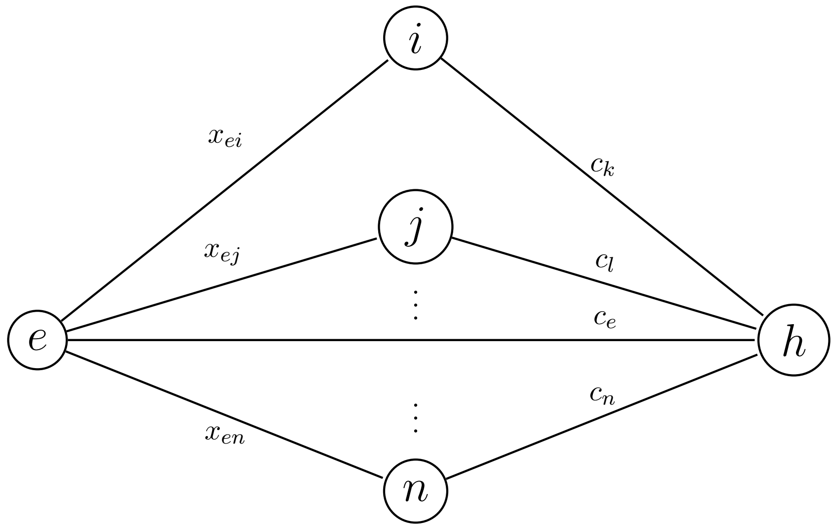


Figure 4.1: An example of an N sector production network without intermediate trade among non-energy commodity sectors.

sector i is

$$\frac{d\mathbf{M}}{d\phi_{ei}}\phi_{ei} = \sum_{k=0}^{\infty} \frac{\partial \mathbf{\Omega}^{*k}}{\partial \phi_{ei}}\phi_{ei} \tag{4.21}$$

Equation (4.21) shows how technological change creates a ripple effect throughout the economy. In the case of energy efficiency improvements, the cascading effect occurs along the energy sector's upstream and downstream supply chains.

Consider the first-order effect of the energy efficiency improvement

$$\frac{\partial \mathbf{\Omega}^{*}}{\partial \phi_{ei}}\phi_{ei} = (\sigma - 1)\,\omega_{ei}^{*}\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}} \tag{4.22}$$

The first-order effect measures the direct impact of an energy efficiency improvement on the economy's multiplier matrix. In this case, the only multiplier affected will be the energy sector's multiplier, captured by the row vector $\mathbf{M}_e$ in the multiplier matrix, because I are ignoring other sectors in the production chain. Analysis using only these direct effects is equivalent to assuming the economy's production network follows the structure in Figure 4.1.

Now, consider the second-order effect of the energy efficiency improvement

$$\begin{aligned}\frac{\partial \boldsymbol{\Omega}^{*2}}{\partial \phi_{ei}} &= \frac{\partial \boldsymbol{\Omega}^{*}}{\partial \phi_{ei}}\boldsymbol{\Omega}^{*} + \boldsymbol{\Omega}^{*}\frac{\partial \boldsymbol{\Omega}^{*}}{\partial \phi_{ei}} \\ &= (\sigma - 1)\,\omega_{ei}^{*}\left(\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}\boldsymbol{\Omega}^{*} + \boldsymbol{\Omega}^{*}\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}\right)\end{aligned} \tag{4.23}$$

Equation (4.23) illustrates the propagation of the efficiency shock through the economy's production network. The terms in parentheses show how the efficiency shock affects the energy sector's multiplier and the energy sector's upstream suppliers' multipliers. The term $\boldsymbol{\Omega}^{*}\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}$ measures the change in the multipliers of upstream suppliers to the energy sector, and the term $\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}\boldsymbol{\Omega}^{*}$ measures the impact on the energy sector's multiplier. In the case of $k = 2$, the derivative measures the impact of the efficiency shock on the multipliers of the energy sector's direct suppliers, and the multiplier for the energy sector is affected by direct purchasers of the more efficient sector's product.

The derivative of higher-order matrices accounts for additional impacts throughout the energy sector's supply chains. Unlike the previous two examples, the derivative of $\boldsymbol{\Omega}^{*k}$ for $k > 2$ yields the impacts of the energy efficiency shock on the multipliers of the energy sector, the indirect suppliers that are $k - 1$ steps upstream from the energy sector, and the indirect purchasers that are $k - 2$ steps downstream from the source sector. The following proposition will prove useful in quantifying the total effects of the energy efficiency improvement on the economy's multiplier matrix

Proposition 2 *For $k > 2$, the derivative of the k-th term of the power series expansion of* $\mathbf{M}$ *is given by*

$$\frac{\partial \boldsymbol{\Omega}^{*k}}{\partial \phi_{ei}} = \frac{\partial \boldsymbol{\Omega}^{*}}{\partial \phi_{ei}}\boldsymbol{\Omega}^{*(k-1)} + \sum_{l=1}^{k-2}\boldsymbol{\Omega}^{*(k-l-1)}\frac{\partial \boldsymbol{\Omega}^{*}}{\partial \phi_{ei}}\boldsymbol{\Omega}^{*l} + \boldsymbol{\Omega}^{*(k-1)}\frac{\partial \boldsymbol{\Omega}^{*}}{\partial \phi_{ei}} \tag{4.24}$$

To show this expression is general, I use proof by induction. Assume Equation (4.24) holds for some $k > 2$. Next, I illustrate that Equation (4.24) holds for $k + 1$ instead. Using the matrix product rule, I can write the derivative of the $k + 1$ term of the power series *expansion as*

$$\frac{\partial \boldsymbol{\Omega}^{*(k+1)}}{\partial \phi_{ei}} = \frac{\partial \boldsymbol{\Omega}^{*k}}{\partial \phi_{ei}} \boldsymbol{\Omega}^* + \boldsymbol{\Omega}^{*k} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}}$$

Substituting equation (4.24) in this expression yields

$$\begin{aligned}
\frac{\partial \boldsymbol{\Omega}^{*(k+1)}}{\partial \phi_{ei}} &= \left(\frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*(k-1)} + \sum_{l=1}^{k-2} \boldsymbol{\Omega}^{*(k-l-1)} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*l} + \boldsymbol{\Omega}^{*(k-1)} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \right) \boldsymbol{\Omega}^* + \boldsymbol{\Omega}^{*k} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \\
&= \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*k} + \boldsymbol{\Omega}^{*((k+1)-1-1)} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^* + \sum_{l=1}^{k-2} \boldsymbol{\Omega}^{k-l-1} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*(l+1)} + \boldsymbol{\Omega}^{*k} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \\
&= \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*k} + \sum_{l=1}^{k+1-2} \boldsymbol{\Omega}^{*(k-l)} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*l} + \boldsymbol{\Omega}^{*k} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}}
\end{aligned}$$

The last statement shows the general form of the $k-th$ order derivative also holds for the derivative of the $k+1$ matrix power and thus completes the proof.

Proposition 2 decomposes the change in the multiplier matrix into direct and upstream impacts. The matrix $\frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}}$ is the direct effect from equation (4.22) and appears in each term of equation (4.24). The direct effect constrains the transmission of the efficiency shock to only along the energy supply chain. The term $\frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*k}$ measures the impact on the energy sector's multiplier, while the term $\boldsymbol{\Omega}^{*k} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}}$ measures the impact on the multipliers of sectors that are $k-1$ steps upstream from the energy sector. Lastly, the middle terms $\boldsymbol{\Omega}^{*(k-l-1)} \frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{ei}} \boldsymbol{\Omega}^{*l}$ account for total supply chain effects in the upstream sectors' multipliers.

After combining (4.22) and (4.24) with (4.21), the change in the multiplier matrix with respect to a 1% energy efficiency shock becomes

$$\frac{d\mathbf{M}}{d\phi_{ei}} \phi_{ei} = (\sigma - 1)\, \omega_{ei}^* \left(\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}} + \boldsymbol{\Pi}_{\phi_{ei}} \right) \tag{4.25}$$

where the elements of $\boldsymbol{\Pi}_{\phi_{ei}} = \sum_{k=2}^{\infty} \frac{\partial \boldsymbol{\Omega}^{*k}}{\partial \phi_{ei}}$ are finite because the sequence $\sum_{k=2}^{\infty} \frac{\partial \boldsymbol{\Omega}^{*k}}{\partial \phi_{ei}}$ con-

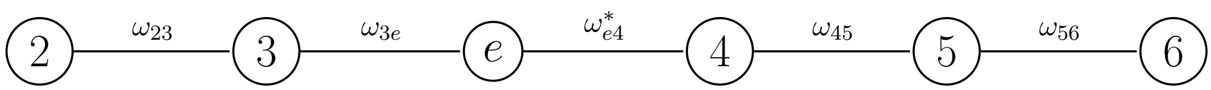


Figure 4.2: Example of a linear economy

verges to 0 given Assumption 1 holds.[4] Equation (4.25) separates the direct and supply chain effects following a productivity shock. Recall, the direct effect $\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}$ is consistent with the network structure in Figure 4.1 and does not consider higher-order linkages between sectors. Hence, this term does not capture supply chain impacts from the energy efficiency improvement. In contrast, the matrix $\boldsymbol{\Pi}_{\phi_{ei}}$ measures the supply chain impacts of the energy efficiency improvement because these higher-order linkages are embedded in the economy's production network.

Example 1 ***(Upstream Transmission)*** *Consider the linear economy given in Figure 4.2. In this example, the efficiency shock occurs in sector 4 and impacts the multipliers of the energy sector's upstream suppliers. Let I^k_{ji} be the measure of influence that i has on j's multiplier in the k-th production stage. The direct effect of the efficiency shock is $\frac{\partial \boldsymbol{\Omega}^*}{\partial \phi_{e4}}$ and only affects the energy sector's multiplier. The energy sector's multiplier changes by an amount $I^1_{e4} = (\sigma - 1)\,\omega^*_{e4}$ due to the efficiency shock.*

Next, consider the second-order impacts $\frac{\partial \boldsymbol{\Omega}^{*2}}{\partial \phi_{e4}}$ of the efficiency shock provided by equation (4.23). The term $\boldsymbol{\Omega}^* \frac{\partial \boldsymbol{\phi}}{\phi_{e2}}$ measures the impact on the energy sector's direct suppliers. In the scenario represented by Figure 4.2, the only direct supplier to the energy sector is sector 3. Sector 3's multiplier is changed by an amount $I^2_{34} = (\sigma - 1)\,\omega_{3e}\omega^*_{e4}$ in this production stage. The term $\frac{\partial \boldsymbol{\phi}}{\phi_{e4}}\boldsymbol{\Omega}^*$ measures the change in the energy sector's multiplier in the second production stage. In this production stage, the energy sector's multiplier changes by an amount $I^2_{e5} = (\sigma - 1)\,\omega^*_{e4}\omega_{45}$, reflecting the influence of indirect downstream industries

[4] This expression can also be written as

$$\frac{d\mathbf{M}}{d\phi_{ei}}\phi_{ei} = -\mathbf{M}\frac{\partial\left[\mathbf{I} - \boldsymbol{\Omega}^*\right]}{\partial \phi_{ei}}\mathbf{M} = (\sigma - 1)\,\omega^*_{ei}\mathbf{M}\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}\mathbf{M}$$

which implies $\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}} + \boldsymbol{\Pi}_{\phi_{ei}} = \mathbf{M}\frac{\partial \boldsymbol{\phi}}{\partial \phi_{ei}}\mathbf{M}$

on the energy sector.

Lastly, consider the changes induced by the third stage of production. Similar to before, the term $\boldsymbol{\Omega}^{*2}\frac{\partial\phi}{\phi_{e2}}$ *is the effect on the energy sector's upstream suppliers, but these suppliers do not interact directly with the energy sector, i.e. these sectors are* $k-1$ *steps upstream from the energy sector. In the example, these suppliers are represented by sector 2. Sector 2's multiplier changes by an amount* $I_{24}^{3}=(\sigma-1)\,\omega_{23}\omega_{3e}\omega_{e4}^{*}$ *in the third-stage of production. The term* $\frac{\partial\phi}{\phi_{e2}}\boldsymbol{\Omega}^{*2}$ *will account for changes in the energy sector's multiplier. The energy's sector multiplier changes by an amount* $I_{e6}^{3}=(\sigma-1)\,\omega_{e4}^{*}\omega_{45}\omega_{56}$ *in the third production stage.*

The linear example economy provides useful insights for evaluating the transmission of energy efficiency shocks in the economy. First, an energy efficiency shock will induce changes along the energy sector's upstream supply chain. The magnitude of these changes will depend on the direct and indirect roles of other sector's in the upstream energy supply chain. Second, the energy sector is directly affected by the efficiency shock. The size of the effect on the energy sector will depend on the role of energy as an intermediate supplier in the source sector's distribution chains. Third, the energy intensiveness of the source sector plays a role in both of these effects. For the remainder of the paper, I will refer to the sector experiencing the efficiency improvement as the *source* sector.

Before turning to the main results, I will briefly highlight the interpretation of changes in $\mathbf{M}^{'}$ from the energy efficiency improvement. Given Assumption 1 is true and using the relation $\boldsymbol{\Omega}^{*'}\ldots\boldsymbol{\Omega}^{*'}\boldsymbol{\Omega}^{*'}=\left(\boldsymbol{\Omega}^{*}...\boldsymbol{\Omega}^{*}\boldsymbol{\Omega}^{*}\right)^{'}$, I can write $\mathbf{M}^{'}=\sum_{k=0}^{\infty}\left(\boldsymbol{\Omega}^{*'}\right)^{k}$ by taking the transpose of (5). Further, because $\frac{\partial\left(\boldsymbol{\Omega}^{*'}\right)^{k}}{\partial\phi_{ei}}=\left(\frac{\partial\boldsymbol{\Omega}^{*k}}{\partial\phi_{ei}}\right)^{'}$, the derivative of the k-th term of the power series expansion is the transpose of equation (4.24). Hence, the change in the transposed multiplier matrix following a 1% energy efficiency shock becomes

$$\frac{d\mathbf{M}^{'}}{d\phi_{ei}}\phi_{ei}=(\sigma-1)\,\omega_{ei}^{*}\left(\frac{\partial\boldsymbol{\phi}}{\partial\phi_{ei}}+\boldsymbol{\Pi}_{\phi_{ei}}\right)^{'} \tag{4.26}$$

Example 2 ***(Downstream Transmission)*** *Again, consider the linear economy represented* *in Figure 4.2. I previously illustrated how energy efficiency shocks translate into upstream impacts. However, energy efficiency changes will also influence downstream sectors. Equation (4.26) captures these downstream effects. Because the expression for $d\mathbf{M}^{'}$is simply $(d\mathbf{M})^{'}$, the direction of influence reverses directions. For instance, the direct effect of the efficiency shock in (4.26) will affect sector 4's multiplier rather than the energy sector's multiplier. Sector 4's multiplier will change by an amount $I^{1}_{4e} = (\sigma - 1)\,\omega^{*}_{e4}$ following the efficiency improvement.*

The results are similar for the second-order effect. The term $\mathbf{\Omega}^{*'}\frac{\partial \mathbf{\Omega}^{*'}}{\partial \phi_{ei}}$ captures the change in the multipliers of sector 4's downstream purchasers. Specifically, this capture the impact on direct purchasers of sector 4's output. In the linear economy example, this impacts sector 5's multiplier. In particular, sector 5's multiplier changes by $I^{2}_{5e} = (\sigma - 1)\,\omega^{*}_{e4}\omega_{45}$ after the efficiency shock. The term $\frac{\partial \mathbf{\Omega}^{*'}}{\partial \phi_{ei}}\mathbf{\Omega}^{*'}$ measures the impact on the source sector's multiplier. In this case, sector 4's multiplier will adjust by $I^{2}_{43} = (\sigma - 1)\,\omega_{3e}\omega^{*}_{e4}$ from the energy efficiency improvement.

Transmission in the third production stage follows a similar pattern. The term $\left(\mathbf{\Omega}^{*'}\right)^{2}\frac{\partial \mathbf{\Omega}^{*'}}{\partial \phi_{ei}}$ will capture the downstream, indirect impacts of the efficiency shock. Sector's that indirectly rely on output from sector 4 will be affected at this production stage. In the example, this is sector 6, and sector 6's multiplier will change by $I^{3}_{6e} = (\sigma - 1)\,\omega^{*}_{e4}\omega_{45}\omega_{56}$ in this stage. Lastly, sector 4's multiplier will adjust in this stage too. In particular, sector 4's multiplier will adjust by $I^{3}_{42} = (\sigma - 1)\,\omega_{23}\omega_{3e}\omega^{*}_{e4}$, reflecting the influence of upstream suppliers of the energy sector.

The preceding example provides the final insight needed to understand how efficiency shocks propagate in the economy. First, energy efficiency shocks will initiate downstream adjustments starting from the source sector. Any sectors directly or indirectly reliant on the source sector's product are exposed to the productivity shock. The magnitude of exposure will depend on the energy sector's indirect role as a supplier of products to these sectors. Second, the source sector will also be impacted by the efficiency shock. As illustrated, the size of the effect will ultimately depend on the role of upstream suppliers in the energy supply chain.

Taken together, the results in this section provide a formal method for decomposing the transmission of energy efficiency shocks in the economy. Specifically, energy efficiency shocks transmit to upstream suppliers of the energy sector and to downstream consumers of the source sector. Even more, the direction of transmission is associated with the changes in the economy's multiplier matrix induced by the productivity shock. These characterizations will play an important role for understanding how the economy's production network affect aggregate energy savings.

The examples in this section set the stage for evaluating how changes in the energy sector's multiplier directly influence energy production in the economy. The examples provide two explanations for the magnitude of these changes. First, in both the upstream and downstream transmission examples, the change in the energy sector's multiplier is proportional to the energy intensiveness ω_{e4} of the source sector's production technology. Second, the source sector's downstream supply chains will also affect the magnitude of changes in the energy sector's multiplier. In each example, the direct and indirect downstream relationships with the source sector, e.g. ω_{45} and $\omega_{45}\omega_{56}$, are components of the changes in the energy sector's multiplier. Therefore, I hypothesize the systemic importance of the source sector as a supplier in the economy is a crucial determinant of aggregate energy savings following an efficiency improvement.

4.5 Energy Savings

In this section, I evaluate the effect of an exogenous, zero-cost energy productivity shock on the equilibrium quantity of energy produced. I start the analysis by briefly introducing the results for partial equilibrium energy savings. The partial equilibrium analysis does not consider price adjustments in other factor and commodity markets. Under this scenario, aggregate energy savings is proportional to the elasticity of substitution and the share of total resource consumption by the more efficient sector.

After presenting the partial equilibrium analysis, I conduct the general equilibrium analysis. I show aggregate energy savings in general equilibrium are determined by a price, growth, and composition channel, and the magnitude of savings created by these channels will depend on structural features of the economy's production network. Moreover, I demonstrate the underlying mechanics of these channels to elucidate the economic intuition behind the mathematical results. After presenting the decomposition results, I show aggregate energy savings can be decomposed into direct and network-driven components. Using these results, I derive the energy savings multiplier and relay the intuition behind the measure.

4.5.1 Partial Equilibrium Analysis

While holding output prices constant, variations in the productivity parameter ϕ_{ei} will directly impact intermediate energy demand in two ways. First, energy efficiency improvements make sectors less energy intensive, as captured by the ω_{ei}/ϕ_{ei} term in equation (4.6a), and thus reduce the quantity of energy produced in the economy. Second, energy production will increase through a reduction in the energy service price.[5] Holding output prices constant, energy savings with respect to a 1% efficiency improvement is expressed as

$$-\frac{dx_{ei}}{d\phi_{ei}}\phi_{ei} = (1-\sigma)\, x_{ei} \tag{4.27}$$

Equation (4.27) is the familiar expression for partial equilibrium energy savings [171, 144, 146]. This result implies that aggregate energy savings are higher when sectors with a

[5] The price $p_{si} = p_e/\phi_{ei}$ is the implicit energy service price given the productivity of sector i's conversion technology. To understand this, consider a scenario where a sector requires processing heating to manufacture its products. The energy productivity parameter ϕ_{ei} summarizes the productivity of the energy conversion technology used to transform raw energy inputs, e.g. kilograms of coal, into useful heat. The parameter ϕ_{ei} is measured in units of BTU/kg of coal, and, consequently, the energy service is measured in BTUs. Combining this parameter with the price of coal p_e, the price of the energy service p_{si} is expressed in units of \$/BTU. Hence, while holding constant coal prices, as the productivity of the conversion technology improves, the energy service price declines and the sector increases consumption of the energy intermediate.

larger share of resources are targeted with energy efficiency policy. Further, the elasticity of substitution determines the sign of energy savings. When the production technology approaches the Leontief limit ($\sigma \to 0$), energy savings from the efficiency improvement increase. In contrast, when input substitution becomes sufficiently flexible ($\sigma > 1$), energy efficiency improvements increase energy consumption in the economy.

4.5.2 General Equilibrium Analysis

With reference to equation (4.6a), it is clear the partial equilibrium setting, i.e. holding output prices constant in the wake of efficiency improvements, does not permit price adjustments in other factor and commodity markets to affect aggregate energy savings. In more general settings, industrial energy efficiency policy may induce price adjustments throughout the economy as markets reach a new equilibrium following the efficiency shock. From the expression in (4.17a), I decompose the change in economy-wide energy consumption from a 1% energy efficiency improvement in sector i into a (i) price effect, (ii) a growth effect, and (iii) a composition effect. Formally, the change in energy production from a 1% energy efficiency improvement is given by

$$\frac{dy_e}{d\phi_{ei}}\phi_{ei} = \underbrace{\frac{\partial p_e^{-\sigma}}{\partial \phi_{ei}} C \boldsymbol{\Upsilon}_e \phi_{ei}}_{\text{Price channel}} + \underbrace{p_e^{-\sigma} \frac{\partial C}{\partial \phi_{ei}} \boldsymbol{\Upsilon}_e \phi_{ei}}_{\text{Growth channel}} + \underbrace{p_e^{\sigma} C \frac{\partial \boldsymbol{\Upsilon}_e}{\partial \phi_{ei}} \phi_{ei}}_{\text{Composition channel}} \tag{4.28}$$

Based on this characterization, aggregate energy savings $\mathcal{S} = -\frac{dy_e}{d\phi_{ei}}\phi_{ei}$ are determined through changes in the market price of the energy commodity, labor income, or the structural role of energy in the economy. As illustrated in Section 3, commodity and factor prices are determined through the structural properties of the economy's production network. Moreover, the structural role of energy is determined by the supplier centrality measure, a variant of Bonacich [166] centrality. Hence, variations in the topology of the production network will directly affect these quantities both directly and indirectly.

The Price Channel

The price channel gives the portion of aggregate energy savings created by a change in the equilibrium energy price while holding household income and the structural role of energy constant. By combining (4.13a) and (4.19), the equilibrium energy price becomes

$$p_e = \left(\frac{\mathbf{\Delta}_e}{\mathbf{\Upsilon}' \boldsymbol{\gamma}} \right)^{\frac{1}{1-\sigma}}$$

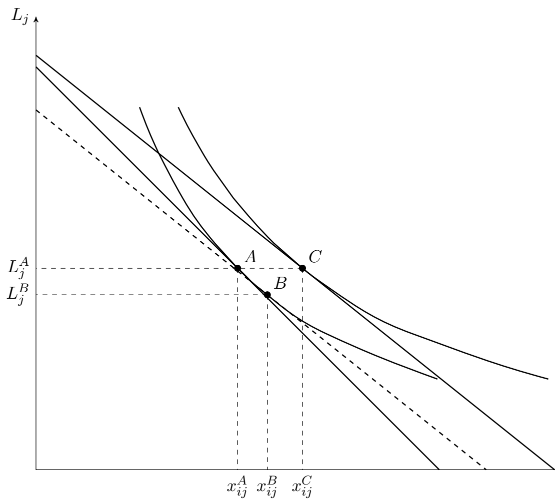
Differentiating this expression with respect to a 1% efficiency improvement and substituting into (4.28) yields the amount of aggregate energy savings from the price channel

$$\mathcal{S}_{\text{price}} = \sigma \omega_{ei}^{*} \left(\frac{\alpha_i + \mathbf{\Pi}_e \boldsymbol{\alpha}}{\mathbf{\Upsilon}_e} \theta_e + \sum_{j \neq e} \frac{\mathbf{\Pi}_j \boldsymbol{\alpha}}{\mathbf{\Upsilon}_j} \theta_j - \frac{\mathbf{\Pi}_e' \boldsymbol{\gamma}}{\mathbf{\Delta}_e} \right) y_e \tag{4.29}$$

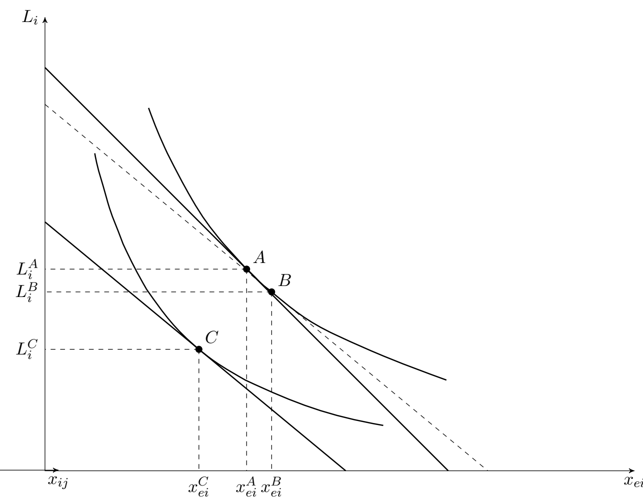
To simplify notation, I will drop the ϕ_{ei} subscript from the supply chain matrix and assume the efficiency shock occurs in sector i for the rest of the paper. Instead, I will use the subscript to denote row vectors. Hence, the object $\mathbf{\Pi}_i$ is the ith row of the supply chain matrix $\mathbf{\Pi}_{\phi_{ei}}$ from (4.25).

The price channel is driven by two counteracting forces: (i) an intensive margin effect and (ii) a wage effect. While holding wage rates constant, the intensive margin effect $\sigma \omega_{ei}^{*} \frac{\mathbf{\Pi}_e' \boldsymbol{\gamma}}{\mathbf{\Delta}_e}$ is driven by a reduction in the energy service price for the source sector, which reduces the source sector's marginal cost. With marginal cost pricing, the lower marginal cost from the negative price shock is reflected in the market price for the source sector's output, thus reducing relative input prices for downstream sectors. As the negative price shock transmits throughout the economy, changes in relative input prices cause a substitution and output effect in downstream industries, spurring an expansionary process in the economy.

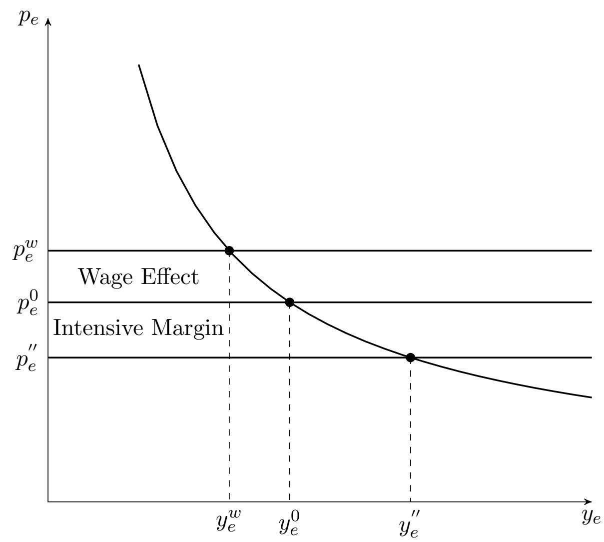
Figure 4.3a depicts the substitution and output effects in downstream industries follow-



(a) Downstream effects (Intensive Margin)



(b) Upstream effects (Wage Effect)



(c) Energy Savings from the Price Channel

Figure 4.3: Energy savings from the price channel decomposed into downstream and upstream effects.

ing the energy-service price shock. The reduction in the energy-service price is reflected in the source sector's output price. For downstream industries, the drop in the source sector's output price makes the source sector's product relatively cheaper than labor or other intermediates. Holding output constant in downstream industries, the reduction in relative input prices induces firms in downstream industries to substitute production processes toward those that favor the cheaper intermediate, depicted as a movement from A to B in 4.3a. At the same time, downstream industries also experience a reduction in the marginal cost of production, which is passed on to purchaser's of their output. Lower market prices trigger a similar substitution effect in other downstream sectors and increases output from B to C.

To the extent the energy sector is downstream from the source sector, input prices for the energy sector may also adjust and induce an expansion within the energy industry. The term $\frac{\mathbf{\Pi}_e^{\prime}\boldsymbol{\gamma}}{\mathbf{\Delta}_e}$ measures the extent to which the energy prices adjust from this process. If the energy sector is a direct or indirect source of demand for the source sector, equation (4.29) stipulates the transmission of the negative price shock through the economy causes energy prices to fall, energy production to expand, and aggregate energy savings to decrease. The intensive margin effect's impact on aggregate energy savings is graphically represented in Figure 4.3c.

Aggregate energy savings are also determined by a wage effect. The wage effect is driven by the upstream transmission of the energy-service price shock. As downstream industries expand, more intermediates must be sourced from the energy sector and the energy sector's suppliers. However, because labor resources are fully employed, labor inputs are relatively scarcer and wages increase. The effect of the efficiency shock on wages is represented by the terms $\frac{\alpha_i+\mathbf{\Pi}_e\boldsymbol{\alpha}}{\mathbf{\Upsilon}_e}\theta_e + \sum_{j\neq e}\frac{\mathbf{\Pi}_j\boldsymbol{\alpha}}{\mathbf{\Upsilon}_j}\theta_j > 0$ in (4.29), where $\theta_i = \frac{L_i}{L} = \frac{\mathbf{\Upsilon}_i\gamma_i}{\mathbf{\Upsilon}^{\prime}\boldsymbol{\gamma}}$ represent employment shares of industries. The upward pressure on wages causes relative factor prices to adjust because wages *and* the market price of upstream intermediates will increase. As the labor market re-calibrates from the demand shock, higher wage rates cause production in upstream industries to scale back.

Figure 4.3b depicts the impacts of rising wage rates on intermediate and labor demand. Higher wages are passed on as higher prices to downstream industries. Holding output constant, the adjustment in relative input prices induces a movement from A to B for downstream industries. Higher input costs are passed on to other downstream industries, reducing the quantity of output demanded in these industries. The net effect is a scaling back of production in upstream sectors, depicted as a movement from x_{ei}^A to x_{ei}^C in 4.3b.

Because the wage effect is positive, energy prices are predicted to increase through the wage mechanism. The higher energy price reduces the quantity of energy demanded in the economy. Hence, aggregate energy savings increase because of higher energy prices. Graphically, the wage effect is represented by an increase in the energy price from p_e^0 to p_e^w in Figure 4.3c. Because income and the structural role of energy are held constant, aggregate demand for energy remains unchanged. Instead, the higher energy price reduces the quantity of energy demanded in the economy, leading to aggregate energy savings.

The Growth Channel

The growth channel measures the amount of aggregate energy savings created by an expansion in household income, holding commodity prices and the structural role of energy constant. Substituting the expression for the growth channel with $C = w\bar{L}$ and setting $\bar{L} = 1$ in (4.28) yields

$$\mathcal{S}_{\text{growth}} = -\omega_{ei}^* \left(\frac{\alpha_i + \mathbf{\Pi}_e \boldsymbol{\alpha}}{\mathbf{\Upsilon}_e} \theta_e + \sum_{j \neq e} \frac{\mathbf{\Pi}_j \boldsymbol{\alpha}}{\mathbf{\Upsilon}_j} \theta_j \right) y_e \tag{4.30}$$

where $\theta_i = \frac{L_i}{L}$ represents the employment share of a sector.

Equation (4.30) stipulates that aggregate energy savings unambiguously declines from the growth channel. Figure 4.4 graphically depicts the growth channel and the impact on aggregate energy savings. Holding commodity prices constant and output constant, the productivity shock generates growth in the economy by reducing the unit labor requirements

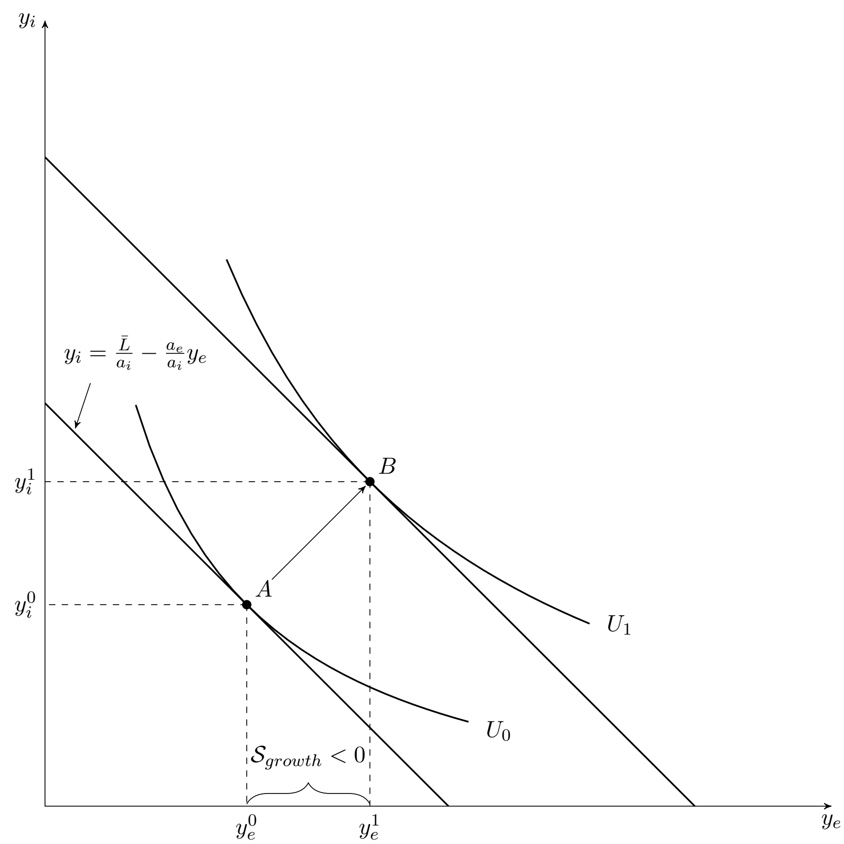


Figure 4.4: Aggregate Energy Savings from the Growth Channel

of industry. Households benefit from this growth through an increase in disposable income and subsequently increase consumption of final goods. In Figure 4.4, this is represented by a shift of the production possibilities frontier outward, where energy consumption shifts from an initial level of y_e^0 to y_e^1.

The Composition Channel

The composition channel measures the change in aggregate energy consumption caused by a change in the structural role of energy in the economy, holding commodity prices and household income fixed. In this context, the structural role of energy refers to the amount of energy embodied in final goods and services in the economy. When the amount of energy embodied in goods and services increases, the structural importance of the energy sector increases, and vice versa. In the model, economy-wide energy savings from the composition channel is given by

$$\mathcal{S}_{\text{composition}} = (1-\sigma)\,\omega_{ei}^{*}\left(\frac{\alpha_i}{\boldsymbol{\Upsilon}_e} + \frac{\boldsymbol{\Pi}_e\boldsymbol{\alpha}}{\boldsymbol{\Upsilon}_e}\right) y_e \tag{4.31}$$

The composition channel is driven by two components. The first component $(1-\sigma)\omega_{ei}^{*}\frac{\alpha_i}{\boldsymbol{\Upsilon}_e}y_e$ measures the change in embodied energy in the source sector's final product sold to the representative household. More importantly, this component of the composition channel is the partial equilibrium energy savings derived in equation (4.27). Partial equilibrium energy savings can be written as

$$(1-\sigma)\,x_{ei} = (1-\sigma)\,\omega_{ei}^{*}p_e^{-\sigma}p_i^{\sigma}y_i$$

Partial equilibrium energy savings do not account for the impact of the source sector's efficiency improvement on intermediate production. Because of this, the source sector's total output y_i can be replaced with c_i above. Hence, partial equilibrium energy savings become

$$\begin{aligned}(1-\sigma)\,x_{ei} &= (1-\sigma)\,\omega_{ei}^{*}p_e^{-\sigma}p_i^{\sigma}c_i \\ &= (1-\sigma)\,\omega_{ei}^{*}p_e^{-\sigma}C\frac{p_i^{\sigma}c_i}{C} \\ &= (1-\sigma)\,\omega_{ei}^{*}\frac{\alpha_i}{\boldsymbol{\Upsilon}_e}y_e\end{aligned}$$

By replacing the parameters in the final expression, partial equilibrium energy savings can be written as

$$(1-\sigma)\,\omega_{ei}^{*}\frac{\alpha_i}{\boldsymbol{\Upsilon}_e}y_e = (1-\sigma)\left(\frac{x_{ei}}{y_e}\right)\left(\frac{c_i}{y_i}\right)y_e$$

This expression measures the energy embodied in the source sector's final product, thus connecting the first component of the composition channel with the concept of embodied energy. Intuitively, if energy production increases by a single unit, this expression stipulates a fraction $\frac{x_{ei}}{y_e}\frac{c_i}{y_i}$ of this increase will go to satisfying final demand in the source sector. A larger fraction implies more energy is embodied in this final product.

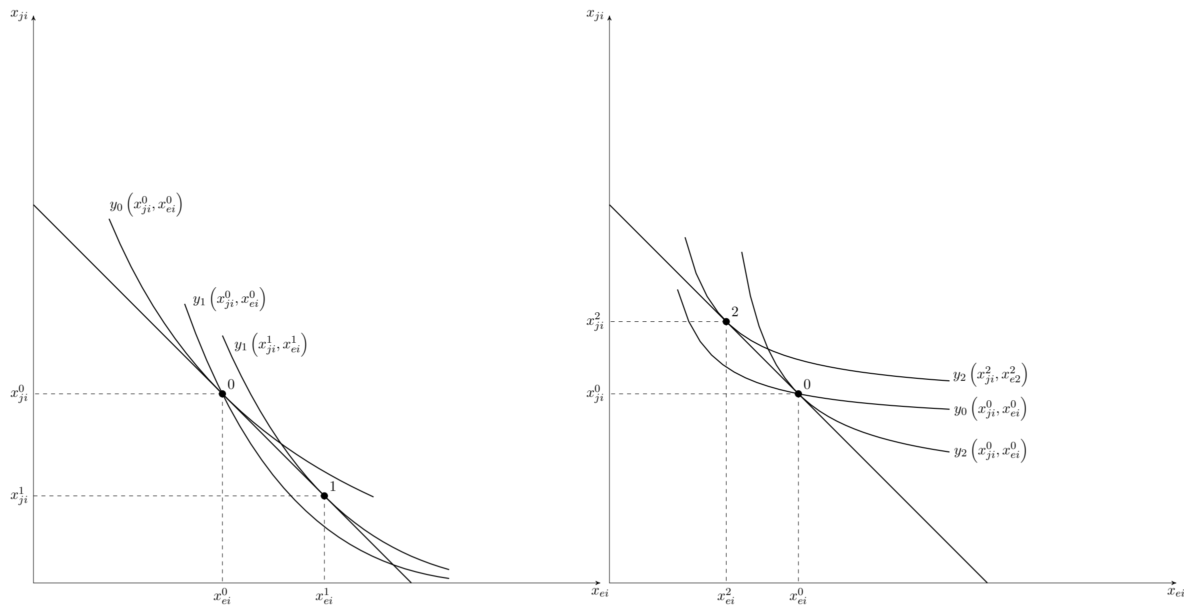
The second component of the composition channel $(1-\sigma)\omega_{ei}^{*}\frac{\mathbf{\Pi}_e\boldsymbol{\alpha}}{\mathbf{\Upsilon}_e}y_e$ measures the amount of energy embodied within the source sector's downstream supply chains. To illustrate this, I will use the linear economy given in Figure 4.2 as an example. In this example, the change in energy production from the second component of the composition channel is

$$\begin{aligned}(1-\sigma)\,\omega_{e4}^{*}\frac{\mathbf{\Pi}_e\alpha}{\mathbf{\Upsilon}_e}y_e &= (1-\sigma)\,\omega_{e4}^{*}\frac{\omega_{45}\omega_{56}\alpha_6}{\mathbf{\Upsilon}_e}y_e \\ &= (1-\sigma)\left(\frac{x_{e4}}{y_e}\right)\left(\frac{x_{45}}{y_4}\right)\left(\frac{x_{56}}{y_5}\right)\left(\frac{c_6}{y_6}\right)y_e\end{aligned}$$

This example illustrates how the second component of the composition channel measures the embodied energy of the source sector's downstream supply chains. When downstream supply chains are more energy intensive, the embodied energy requirements are larger, and the model predicts energy savings from the composition channel will be larger when there is less scope for input substitution.

I graphically represent the mechanics of the composition channel in Figure 4.5 for two separate cases. The cases correspond to different assumptions regarding the scope for input substitution in the source sector. Figure 4.5a corresponds to a case where input substitution is more flexible, i.e. $\sigma > 1$, and Figure 4.5b corresponds to a case with minimal opportunities for input substitution, i.e. $\sigma < 1$. The figures plot the equilibrium input bundles before and after the efficiency shock, while holding factor and commodity prices constant.

Figure 4.5a shows the mechanics of the composition channel when producers can substitute inputs with minimal frictions. The efficiency shock has the effect of changing the technical rate of substitution between inputs for producers in the source sector. In this case, this changes the shape of the isoquant from y_0 to y_1. At the initial equilibrium input bundle (x_{ei}^0, x_{ji}^0), producers in the source sector can produce $y_1(x_{ei}^0, x_{ji}^0)$ for the same cost as pro-



(a) $\sigma > 1$ (b) $\sigma < 1$

Figure 4.5: The composition channel

ducing $y_0(x_{ei}^0, x_{ji}^0)$. However, if the source sector producers were to re-allocate their input selection from Point 0 to Point 1, they are able produce more output for the same cost, increasing profits in the sector. When $\sigma > 1$, the figure illustrates the source sector will re-allocate the input selection to favor the energy intermediate. After re-allocating inputs in favor of the energy intermediate, production in the source sector becomes more energy intensive, and, consequently, this re-allocation increases the embodied energy of the sector's downstream supply chains. When this happens, energy savings from the efficiency shock are offset, and economy-wide energy consumption increases.

Figure 4.5b illustrates the economic intuition for the opposite scenario. When there is little opportunity for input substitution, the efficiency shock creates an incentive for producers to re-allocate input bundles in favor of non-energy intermediates. The logic is similar for the flexible substitution case. The efficiency shock alters the source sector's production technology, changing the technical rate of substitution between inputs. The isoquant changes from y_0 to y_2. If producers consume the initial input bundle (x_{ei}^0, x_{ji}^0), they are not utilizing resources efficiently. In particular, if source sector producers re-allocate input selections to favor the non-energy intermediate, i.e. (x_{ei}^2, x_{ji}^2), they can increase production while maintaining the same cost. In this scenario, the embodied energy within the source sector's supply chains declines because producers have become less energy intensive. Consequently, energy savings from the efficiency shock will increase.

4.5.3 The Energy Savings Multiplier

The previous section decomposed aggregate energy savings into three channels and provided the economic intuition behind the results. Even more, I illustrated the magnitude of these channels are determined by the structure of the economy's production network. In this section, I introduce a simple measure for quantifying the importance of production networks for aggregate energy savings following an efficiency shock. Specifically, the *energy savings multiplier* (ESM) measures the additional gains (or losses) from an efficiency shock caused by re-allocation within the production network.

The ESM is computed by decomposing aggregate energy savings into direct and network-driven energy savings. Consider the expressions for energy savings from the price, growth, and composition channels in (4.29), (4.30), and (4.31), respectively. Direct energy savings from these channels are given by

$$\mathcal{S}_{price}^{direct} = \sigma \omega_{ei}^* \frac{\alpha_i}{\mathbf{\Upsilon}_e} \theta_e y_e, \quad \mathcal{S}_{growth}^{direct} = -\omega_{ei}^* \frac{\alpha_i}{\mathbf{\Upsilon}_e} \theta_e y_e, \quad \mathcal{S}_{composition}^{direct} = (1-\sigma)\, \omega_{ei}^* \frac{\alpha_i}{\mathbf{\Upsilon}_e} y_e$$

Direct energy savings do not account for the higher-order impacts of the production network. Instead, direct energy savings only accounts for the role of the energy sector as a direct supplier to the source sector, e.g. see Figure 4.1. Combining these expressions shows direct energy savings will be proportional to to the share of resource consumption of the source sector. Total direct energy savings is given by

$$\mathcal{S}^{direct} = (1-\sigma)\,(1-\theta_e)\,\eta_i \tag{4.32}$$

where $\eta_i = \frac{x_{ei}}{y_e}$ represents the source sector's share of energy consumption. Direct energy savings are larger when the sector targeted with the energy efficiency policy represent a higher share of total energy consumption. Even more, direct energy savings are higher when the elasticity of substitution between inputs is smaller. If $\sigma > 1$, then energy consumption in the economy will increase following the efficiency shock. Lastly, if the energy sector is a major source of employment in the economy, energy savings will be lower, regardless of the characteristics of the source sector.

The remaining terms from each of these channels reveal the impacts of the production network on aggregate energy savings. Let $\upsilon_i = \omega^*_{ei}\frac{\mathbf{\Pi}_i\boldsymbol{\alpha}}{\mathbf{\Upsilon}_i}$ and $\delta_e = \omega^*_{ei}\frac{\mathbf{\Pi}'_e\gamma}{\mathbf{\Delta}_e}$ represent the network-driven components of general equilibrium energy savings. Then, the network components of the price, growth, and composition channels can be written as

$$\mathcal{S}^{network}_{price} = \sigma\left(\sum_{j=e}^{N}\upsilon_j\theta_j - \delta_e\right)y_e, \quad \mathcal{S}^{network}_{growth} = -\sum_{j=e}^{N}\upsilon_j\theta_j y_e, \quad \mathcal{S}^{network}_{composition} = (1-\sigma)\,\upsilon_e y_e$$

Combining these expressions implies the amount of general equilibrium energy savings driven by the economy's production network is

$$\mathcal{S}^{network} = \left[(1-\sigma)(1-\theta_e)\,\upsilon_e + (\sigma-1)\sum_{j\neq e}\upsilon_j\theta_j - \sigma\delta_e\right]y_e \tag{4.33}$$

The first term in the brackets has a similar interpretation to the total direct energy savings. Comparing the two expressions, it is straightforward to see the share of resource consumption η_i of the source sector in (4.32) is replaced with υ_e in (4.33). The value of υ_e measures the amount of energy embodied in the final goods produced by industries located downstream from the source sector. If the source sector does not supply inputs to downstream industries (as in Figure 4.1), then this term would be equivalent to direct energy savings. The additional terms in the expression for network-driven energy savings capture the additional supply chain impacts that manifest through the intensive margin effect, wage effect, and growth channel.

Using the expressions for direct and network-driven energy savings in (4.32) and (4.33), I can decompose the general equilibrium component of aggregate energy into direct and network-driven components. Specifically, aggregate energy savings can be written as

$$\mathcal{S} = \mathcal{S}^{direct} + \mathcal{S}^{network} \tag{4.34}$$

With aggregate energy savings decomposed into direct and network-driven components, I can construct the ESM that captures the additional gains or losses caused by the economy's production network. The ESM is constructed as

$$\text{ESM} = \frac{\mathcal{S}}{\mathcal{S}^{direct}} = 1 + \frac{\mathcal{S}^{network}}{\mathcal{S}^{direct}} \tag{4.35}$$

The ESM can be positive or negative depending on the elasticity of substitution and the size of energy savings caused by the network. Table 4.1 summarizes the interpretation of the ESM for different values of the elasticity of substitution. Direct energy savings given by (4.32) will be positive or negative depending on whether the elasticity of substitution is below or above unity. When $\sigma > 1$, direct energy savings are negative, and this information can be utilized to infer the impact of the production network on energy savings. The first column of Table 4.1 summarizes the impact of the production network on energy savings when the elasticity of substitution exceeds unity. When ESM < 1, re-allocation within the network increases general equilibrium energy savings, but, when ESM > 1, network-driven energy savings are negative and reduce the gains from the efficiency improvement. Only in the case of $\sigma > 1$ and ESM < 0 are network-driven energy savings large enough to offset the increase in energy consumption from the direct effect, making general equilibrium energy savings positive.

The second column of Table 4.1 summarizes the implications for network-driven energy savings when $\sigma < 1$ and direct energy savings are positive. In this scenario, network-driven energy savings are negative if ESM < 1, but direct energy savings offset the losses

Table 4.1: Value of the Energy Savings Multiplier and Network-Driven Energy Savings

	$\sigma > 1$	$\sigma < 1$
ESM < 0	$\mathcal{S}^{network} > 0,\ \mathcal{S} > 0$	$\mathcal{S}^{network} < 0,\ \mathcal{S} < 0$
$0 <$ ESM < 1	$\mathcal{S}^{network} > 0,\ \mathcal{S} < 0$	$\mathcal{S}^{network} < 0,\ \mathcal{S} > 0$
ESM > 1	$\mathcal{S}^{network} < 0,\ \mathcal{S} < 0$	$\mathcal{S}^{network} > 0,\ \mathcal{S} > 0$

introduced by the network when $0 <$ ESM < 1; otherwise, the network creates a negative multiplier effect and reduces the effectiveness of energy efficiency improvements. When ESM > 1, network-driven energy savings are positive and greater than the direct energy savings, creating a positive multiplier effect for the original energy efficiency improvement.

4.6 Application

In this section, I simulate the impact of exogenous, industrial energy efficiency shocks to provide initial estimates of the energy savings multiplier and connect the magnitude of the multiplier to the Bonacich centrality of the source sector. To this end, I collect proprietary data on input-output networks for the 50 states in the United States for the year 2015 from the IMPLAN Group (IMPLAN). The IMPLAN datasets cover more than 500 sectors for each state, thus providing a rich disaggregation to investigate the impact of input-output networks on aggregate energy savings.

4.6.1 Calibration

The production system is characterized by exogenously given input-output relationships between sectors $\mathbf{\Omega}$, the share of labor in each sector $\boldsymbol{\gamma}$, and the share of each sector's output in final consumption $\boldsymbol{\alpha}$. To calibrate these parameters of the model using the IMPLAN data, I normalize industry prices $\mathbf{P}$, the economy's wage rate w, the economy's labor force $\bar{L}$, and the consumer price index P_c to be equal to 1. Additionally, I take the across industry elasticity of substitution σ to be a known constant. Given this normalization, the model can be calibrated using the available input-output data for each state.

The Input-Output Network

Perhaps the most important component of the model is the input-output matrix $\mathbf{\Omega}$ and calibrating the paramaters in this matrix requires sector prices are equal to their steady-state values. In other words, the steady-state condition $\mathbf{P} = \mathbf{1}$ ensures the input-output matrix can be calibrated using the IMPLAN data. Specifically, under this steady-state condition, I have $\mathbf{\Omega} = \mathbf{D}$.

To see this, consider the equation for intermediate demand given in equation (4.6a). Assume $\phi_{ei} = 1$ and re-arrange this equation to solve for the input-output coefficient ω_{ei}. Under the steady-state condition $\mathbf{P} = \mathbf{1}$, I have the following identity that is used to calibrate the input-output matrix

$$\begin{aligned}\omega_{ei} &= \frac{p_e^{\sigma} x_{ei}}{p_i^{\sigma} y_i} \\ &= \left(\frac{p_e x_{ei}}{p_i y_i}\right)^{\sigma} \left(\frac{x_{ei}}{y_i}\right)^{1-\sigma} \\ &= a_{ei}^{\sigma} \left(\frac{p_e x_{ei}}{p_i y_i}\right)^{1-\sigma} \\ &= d_{ei}\end{aligned}$$

Hence, I can use the direct requirements matrix $\mathbf{D}$ calculated from the IMPLAN data to calibrate the input-output coefficient matrix $\mathbf{\Omega}$ in the model. Importantly, in the simulation, energy efficiency shocks will be applied to the direct requirements matrix $\mathbf{D}$ to simulate changes in energy production for each state.

Labor Shares

I also use the IMPLAN data to calibrate the labor share parameters $\boldsymbol{\gamma}$ in the model. The approach is similar to the method for calibrating the input-output matrix. Equilibrium in the model implies the conditional factor demand for labor in sector i is given by equation

(4.18). Given $w = 1$ and $\mathbf{P} = \mathbf{1}$ in the steady-state, re-arranging the expression for conditional factor demand to solve for the labor share parameter γ_i implies the following

$$\begin{aligned}\gamma_i &= \frac{w^\sigma L_i}{p_i^\sigma y_i} \\ &= \left(\frac{wL_i}{p_i y_i}\right)^\sigma \left(\frac{L_i}{y_i}\right)^{1-\sigma} \\ &= g_i^\sigma \left(\frac{wL_i}{p_i y_i}\right)^{1-\sigma} \\ &= g_i\end{aligned}$$

Thus, assuming wages and sector prices are equivalent to their steady-state values, I can use the labor expenditure shares for the sectors, denoted as an $N \times 1$ vector $\mathbf{g}$, to calibrate the labor intensity parameters $\boldsymbol{\gamma}$ in the model.

Consumption Shares

The final set of model parameters, consumption shares $\boldsymbol{\alpha}$, are calibrated using a similar approach as above. Consider the expression for final consumption in equation (4.3). Re-arranging this equation to solve for the consumption share of sector i and incorporating the steady-state condition for prices implies

$$\begin{aligned}\alpha_i &= \frac{p_i^\sigma c_i}{C} \\ &= \left(\frac{p_i c_i}{C}\right)^\sigma \left(\frac{c_i}{C}\right)^{1-\sigma} \\ &= a_i^\sigma \left(\frac{p_i c_i}{C}\right)^{1-\sigma} \\ &= a_i\end{aligned}$$

Given the steady-state conditions, I can use the household's budget shares, denoted as the $N \times 1$ vector $\mathbf{a}$, to calibrate the household preferences parameters in the model.

4.6.2 Simulation

Once the model is calibrated to data, I can compute the multiplier matrix of the economy and simulate the effects from an energy efficiency shock. For the simulation, I consider efficiency improvements that affect production in three energy-related sectors: (i) Coal Mining (NAICS 212111-212113), (ii) Petroleum Refineries (NAICS 324110), and (iii) Natural gas distribution (NAICS 221210). For the sake of policy relevance and parsimony, I restrict the simulation to efficiency shocks that reduce the direct input requirements of the following highly, energy-intensive industries: (i) Coal Mining $\rightarrow$ Iron and Steel Mills and Ferroalloy Manufacturing (NAICS 331110), (ii) Petroleum Refineries $\rightarrow$ Truck Transportation (NAICS 484110-484230), and (iii) Natural gas distribution $\rightarrow$ Nitrogenous fertilizer manufacturing (NAICS 325311).

Energy production is computed using the calibrated model parameters. Given the underlying data is in steady-state, baseline energy production levels are computed as

$$\tilde{y}_e^0 = [\mathbf{I} - \mathbf{D}]_e^{-1} \mathbf{a} = \tilde{\boldsymbol{\Upsilon}}_e \tag{4.36}$$

where $\tilde{y}_e^0$ is the simulated, baseline production for each energy sector e, and $\tilde{\boldsymbol{\Upsilon}}_e$ is the energy sector's simulated supplier centrality measure. In the simulation, I apply a 10% energy efficiency improvement to each sector by shocking the direct requirements matrix. Importantly, I only consider one shock at a time. The productivity-adjusted direct requirements matrix $\boldsymbol{\phi}^{\sigma-1} \odot \mathbf{D} = \mathbf{D}^*$ accounts for the 10% energy efficiency improvement through the multiplication of $\boldsymbol{\phi}^{\sigma-1}$ and $\mathbf{D}$. Specifically, the e, i-th entry in $\mathbf{D}^*$ becomes $(1.1)^{\sigma-1}\omega_{ei}$ for a given value of σ after the efficiency shock is applied

Energy production after the shock is computed by replacing the direct requirements matrix $\mathbf{D}$ in equation (4.36) with the productivity-adjusted version. However, the efficiency shock will have the effect of shocking prices and household income from their steady-state values. This implies energy production after the shock can be computed numerically using the following expression

$$\tilde{y}_e^1 = \frac{\tilde{\mathbf{\Delta}}_e^{*\frac{\sigma}{\sigma-1}} \tilde{\mathbf{\Upsilon}}_e^*}{\tilde{\mathbf{\Upsilon}}^{*\prime} \mathbf{g}} \tag{4.37}$$

where $\tilde{y}_e^1$ is the simulated energy production after the shock, $\tilde{\mathbf{\Delta}}_e^*$ is the energy sector's simulated consumer centrality after the shock, and $\tilde{\mathbf{\Upsilon}}^*$ is the simulated vector of supplier centrality in the economy. After new energy production is computed, energy savings in the model can be calculated by taking the difference in energy production before and after the shock. Aggregate energy savings $\tilde{S} = y_e^0 - y_e^1$ is then computed by applying shocks to the sectors mentioned above for each state.

To calculate direct energy savings, I simulate equation (4.32) using the calibrated model parameters. The simulated direct energy savings in the model are

$$\tilde{\mathcal{S}}^{direct} = (1-\sigma)\left(1-\tilde{\theta}_e\right) d_{ei} \frac{a_i}{\tilde{\mathbf{\Upsilon}}_e} \tilde{y}_e^0 \tag{4.38}$$

where $\tilde{\theta}_e = \frac{g_e \tilde{y}_e^0}{\mathbf{gi}}$ is the energy's sector's employment share

Lastly, I calculate the ESM by taking the ratio of simulated energy savings and direct energy savings. Formally, I compute the simulated $\widehat{\text{ESM}}$ as follows

$$\widehat{\text{ESM}} = \frac{\tilde{\mathcal{S}}}{\tilde{\mathcal{S}}^{direct}} \tag{4.39}$$

4.6.3 Results

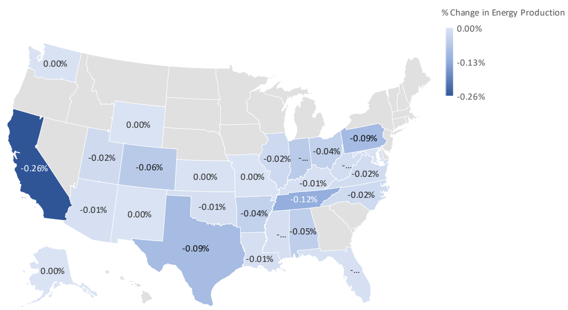
I present the main results of the simulation exercise in this section. I begin by introducing the simulated output elasticities for each major energy sector by state. There are two important insights from these results. First, there is a substantial degree of heterogeneity in the simulated output elasticities. Further, the highest output elasticities do not necessarily correspond to major energy producing states. Second, I find the sign of the simulated output elasticity is highly sensitive to the choice of elasticity of substitution. To determine the cause of this sensitivity, I investigate the impact of the price, growth, and composition channels on the output elasticity.

I decompose energy savings into the price, growth, and composition channels. After comparing the contribution of each channel to overall energy savings, I find the composition channel dominates the price and growth channels in each scenario. The choice of the elasticity of substitution determines whether the composition channel increases or decreases energy savings, and this offers an explanation for why energy savings are sensitive to the elasticity of substitution. The magnitude of savings from the composition channel suggests changes in the embodied energy of the source sector's downstream supply chains has a non-trivial effect on overall energy savings. I explore the role of the production network for energy savings when I present the simulated energy savings multipliers.

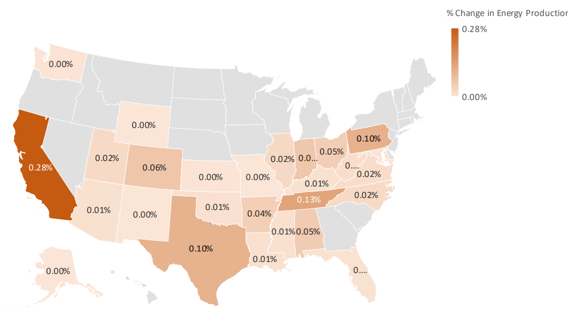
The simulated energy savings multipliers exhibit substantial heterogeneity. For some states, the ESM exceeds unity, indicating that the economy's production network magnified the original efficiency improvement. The importance of networks for amplifying or curtailing energy savings is investigated in this section as well. I provide some preliminary evidence that links the size of the ESM with the supplier centrality of the source sector. I find this relationship holds for each scenario.

Output Elasticities

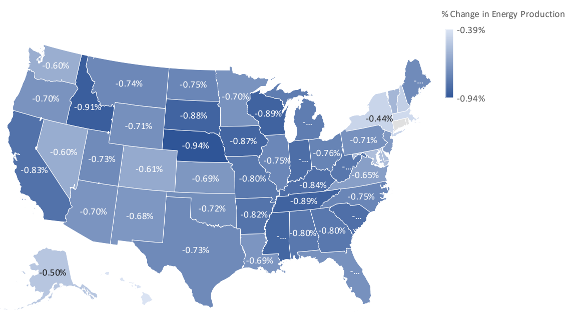
I introduce a 10% efficiency improvement and report the results. Figure 4.6 shows the simulated percentage change in production for each energy sector by state. Reductions (positive energy savings) are colored in blue, and increases (negative energy savings) are colored in orange. For comparison, I include two scenarios that correspond to cases where input substitution is rigid ($\sigma = 0.25$) or flexible ($\sigma = 1.75$). The results are presented in percentage change format to facilitate interpretation of the results as output elasticities. I also present the results for the highest and lowest output elasticities for each simulation in Table 4.2. The corresponding states are listed to facilitate comparison across scenarios, and these states are the focus of the discussion in the following sections.



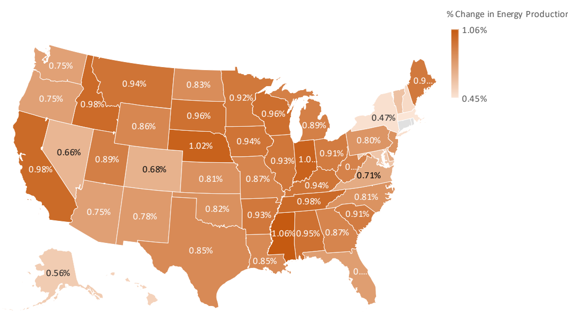
(a) Change in Coal Consumption ($\sigma = 0.25$)



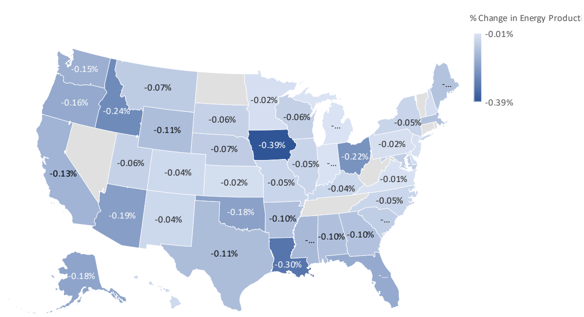
(b) Change in Coal Consumption ($\sigma = 1.75$)



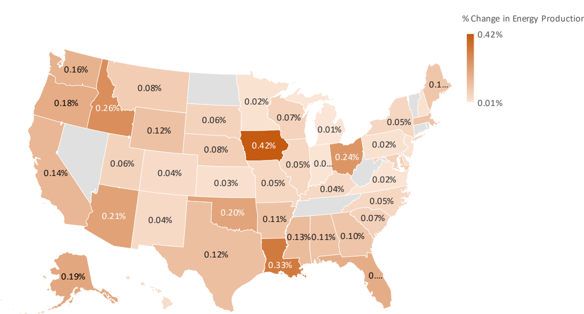
(c) Change in Oil Consumption ($\sigma = 0.25$)



(d) Change in Oil Consumption ($\sigma = 1.75$)



(e) Change in Gas Consumption ($\sigma = 0.25$)



(f) Change in Gas Consumption ($\sigma = 1.75$)

Figure 4.6: Change in Energy Consumption by State

Table 4.2: Highest and lowest output elasticities by simulation

	Rigid Scenario ($\sigma = 0.25$)		Flexible Scenario ($\sigma = 1.75$)	
	Top 3 States	Bottom 3 States	Top 3 States	Bottom 3 States
Coal Mining	1. Tennessee (-0.120%) 2. Pennsylvania (-0.091%) 3. Texas (-0.089%)	1. Wyoming (-0.00038%) 2. Alaska (-0.00067%) 3. Missouri (-0.00077%)	1. Tennessee (0.129%) 2. Pennsylvania (0.103%) 3. Texas (0.102%)	1. Wyoming (0.0005%) 2. Alaska (0.0008%) 3. Missouri (0.0008%)
Petroleum Refineries	1. Nebraska (-0.941%) 2. Idaho (-0.907%) 3. Tennessee (-0.887%)	1. New York (-0.440%) 2. Alaska (-0.498%) 3. Nevada (-0.599%)	1. Mississippi (1.056%) 2. Nebraska (1.021%) 3. Indiana (1.016%)	1. New York (0.474%) 2. Alaska (0.563%) 3. Nevada (0.657%)
Natural Gas Distribution	1. Louisiana (-0.302%) 2. Idaho (-0.245%) 3. Ohio (-0.223%)	1. Michigan (-0.009%) 2. Indiana (-0.013%) 3. Virginia (-0.015%)	1. Louisiana (0.325%) 2. Idaho (0.264%) 3. Ohio (0.241%)	1. Michigan (0.009%) 2. Indiana (0.014%) 3. Virginia (0.016%)

Notes: The table presents the top and bottom 3 output elasticities for each scenario and simulation. States without energy production data collected from the Energy Information Administration are excluded from the rankings. In each scenario, I rank states based on the absolute value of the output elasticity.

From the coal simulation with rigid input substitution, Tennessee (-0.120%), Pennsylvania (-0.091%) and Texas (-0.089%) represent the three states with the highest output elasticities. Pennsylvania and Texas are among the top coal producing states in 2015, collectively accounting for more than 10% of total U.S. coal production. However, Tennessee ranks much lower in terms of total coal production, only accounting for around 0.1% of total U.S. coal production in 2015 [172].[6] In contrast, the nation's largest coal producing state, Wyoming (-0.0004%), has the lowest output elasticity in this scenario. Wyoming accounted for 41.89% of total U.S. coal production in 2015. Total energy savings from the efficiency improvement could have been larger by choosing an alternative policy for Wyoming.

Coal production in the flexible input substitution scenario increases for every state, but the ranking of output elasticities remains relatively constant. Specifically, Tennessee (0.13%), Texas (0.10%), and Pennsylvania (0.10%) are the top three states in terms of output elasticities. The positive sign on the output elasticity implies the efficiency improvement backfires and increases coal production across these states. Wyoming takes the position with the lowest output elasticity in this scenario. In this scenario, backfire from the efficiency improvement could be reduced by targeting different sectors for Tennessee,

[6] Even though it has the largest impacts, I exclude California from the top three states because coal production data is not available for California from the Energy Information Administration. Additionally, total U.S. coal production in 2015 was 896,941 thousand short tons.

Texas, and Pennsylvania.

I find the top three states for output elasticities are Nebraska (-0.94%), Idaho (-0.91%), and Tennessee (-0.89%) for the rigid substitution scenario in the oil simulation. These states, however, account for less than 0.1% of total crude oil production in the U.S. for 2015 [173]. The states with the lowest output elasticities (in absolute value) are New York (-0.44%), Alaska (-0.50%), and Nevada (-0.60%). Alaska accounts for around 10% of total crude oil production in 2015; whereas, New York and Nevada combined only represent 0.02% of production. In this scenario, the distribution of output elasticities is less varied than the coal simulation.

The ranking in the flexible substitution scenario in the oil simulation changes slightly. The states with the highest output elasticities are Mississippi (1.06%), Nebraska (1.02%), and Indiana (1.02%). Collectively, these states account for 0.87% of U.S. crude oil production in 2015. However, the next highest output elasticity is for California (0.98%), which accounted for almost 6% of U.S. crude oil production. The lowest output elasticities in this scenario are New York (0.47%), Alaska (0.56%), and Nevada (0.66%). For this scenario, the energy efficiency improvement backfires across all states, but the backfire could be reduced by choosing a policy that reduces the output elasticity in major energy producing states.

In the natural gas scenario, Louisiana (-0.39%), Idaho (-0.24%), and Ohio (-0.24%) round out the top three states with the largest output elasticities in the rigid scenario. These states account for 16% of (marketed) U.S. natural gas production in 2015 [174]. The states with the smallest output elasticities are Michigan (-0.018%), Indiana (-0.013%), and Virginia (-0.015%). These states contribute less than 1% to U.S. natural gas production in 2015. In the flexible scenario, Louisiana (0.33%), Idaho (0.26%), and Ohio (0.24%) have the highest output elasticities, and Michigan (0.009%), Indiana (0.014%), and Virginia (0.016%) are the states with the lowest elasticities.

Taken together, the simulated output elasticities provide two important insights for how micro-scale energy efficiency improvements materialize at the aggregate level. First, the sign of the output elasticity is sensitive to the choice of elasticity of substitution. When input substitution is rigid, energy savings are positive; however, when input substitution is more flexible, energy efficiency policies backfire and energy consumption increases in the economy. This holds for even a modest difference in the elasticity of substitution. Second, output elasticities vary across states. Variations in the output elasticity are informative with regard to the overall performance of the efficiency improvement. In some scenarios, energy efficiency improvements within major energy producing regions do not necessarily translate into the highest output elasticities. When input substitution is rigid, this suggests the energy efficiency improvements could be adapted to target alternative sectors to raise the overall output elasticity of the state. Alternatively, when input substitution is flexible, targeting alternative sectors could reduce potential backfire from the efficiency improvement. In the next section, I unpack these results further to demonstrate how the price, growth, and composition channels contribute to the heterogeneity in output elasticities.

Channels

Figures 4.7-4.9 summarize the contribution of the general equilibrium channels to the estimated output elasticities from the previous section. In Table 4.3, I compare the results between the highest and lowest output elasticities for each simulation. For the coal and oil simulations, I select the states with the lowest output elasticities based on the contribution of these regions to total energy production in the United States in 2015. For the gas simulation, Louisiana is a top regional producer and the state with the largest output elasticity. In this scenario, I choose the state with the lowest output elasticity for comparison. I report the results as a share of the total output elasticity. This way the counterfactual output elasticity for each channel can be computed by multiplying the total output elasticity by the contribution of each particular channel.

For the sake of parsimony, I will only discuss the results for the rigid input substi-

Table 4.3: Decomposition of the output elasticities into the price, growth, and composition channels

		Rigid Scenario ($\sigma = 0.25$)				Flexible Scenario ($\sigma = 1.75$)			
	State	Output Elasticity	Price	Growth	Composition	Output Elasticity	Price	Growth	Composition
2*Coal Mining	Tennessee	-0.120%	-0.002%	-0.002%	100.004%	0.1294%	0.0105%	0.002%	99.987%
	Wyoming	-0.00038%	-1.810%	-2.867%	104.677%	0.0005%	10.540%	2.385%	87.076%
2*Petroleum Refineries	Nebraska	-0.941%	-0.0643%	-0.230%	100.292%	1.021%	0.446%	0.228%	99.320%
	Alaska	-0.498%	0.2004%	-3.346%	103.129%	0.563%	-1.335%	3.184%	98.141%
2*Natural Gas Distribution	Louisiana	-0.302%	0.0639%	-0.336%	100.271%	0.325%	-0.446%	0.336%	100.111%
	Michigan	-0.009%	0.113%	-0.6609%	100.548%	0.009%	-0.790%	0.658%	100.132%

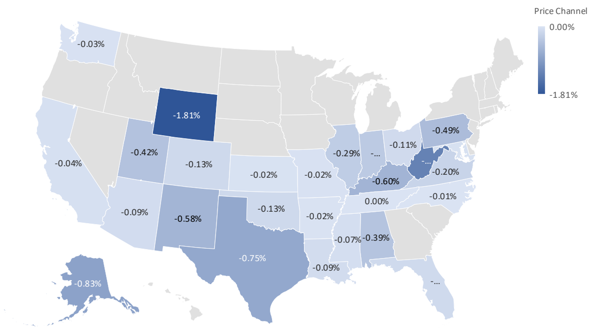
Notes: This tables decomposes the output elasticity into the price, growth, and composition channels. The results are reported to contrast the highest and lowest output elasticities from each simulation.

tution scenario, but I have included the results for the flexible scenario for comparison. For the coal simulation, Wyoming leads with the highest impacts for each channel. However, from Section 4.6.3, I illustrated that Wyoming also has the lowest output elasticity in this scenario. The reason for this is evident by decomposing the output elasticity into the underlying channels. Wyoming has the largest energy savings from the composition channel, suggesting the output elasticity would have been approximately 5% higher had factor and commodity prices remained at baseline values. However, the energy efficiency improvement had the effect of decreasing regional coal prices while simultaneously increasing household income through labor market adjustments. These adjustments in factor and commodity markets increased energy production overall and erased most of the energy savings from the composition channel. In comparison with Tennessee, the price and growth channels are particularly large and can explain why Wyoming realized very minimal aggregate energy savings from the efficiency improvement.

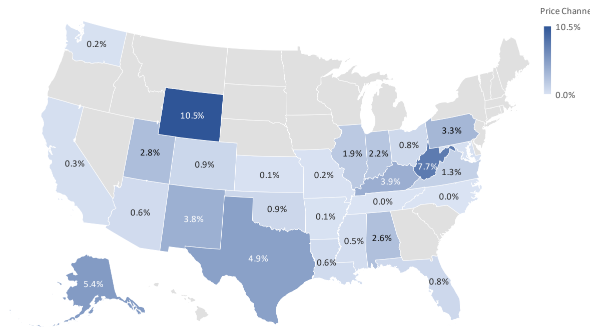
For the oil simulation, I will focus on the results for Alaska because the state accounts for 10% of national crude oil production and was among the lowest output elasticities in the rigid scenario in Section 4.6.3. First, I find the wage effect dominates the intensive margin effect and crude oil prices increase. The increase in regional oil prices, all else constant, leads to a reduction in crude oil. Second, from the growth channel results, I find household re-spending effects are large enough to offset the savings from the price channel and, consequently, overall crude oil production increases. Third, the change in the composition of the input-output network away from energy-intensive goods is large enough to offset the increase in production from the growth channel, but the net effect on the crude oil output elasticity in the state is modest. This suggests targeted interventions in the state would benefit from closer examination of how to minimize household re-spending effects.

From Section 4.6.3, the top states in terms of output elasticities for the rigid scenario accounted for 16% of U.S. natural gas production in 2015. Of these states, the state with the highest output elasticity, Louisiana, accounted for the bulk of this contribution, producing roughly 13% of total U.S. natural gas production in 2015. Decomposing the elasticity reveals why the efficiency improvement was so successful for Louisiana. In terms of the composition effect, Louisiana (100.3%) ranks among the lowest states in the simulation, e.g. the state with the largest composition effect is Ohio (100.8%). However, the effectiveness of the efficiency improvement is boosted by the combination of positive energy savings from the price channel and modest reductions in savings through the growth channel. I find the wage effect dominates the intensive margin effect, generating positive impacts through the price channel (0.06%) in Louisiana. Furthermore, the gains from the price channel and composition channel are only partially offset through household re-spending effects from the growth channel (-0.3%). Hence, the combination of increased energy prices, moderate re-spending impacts, and a structural shift of the economy to less energy-intensive products improve the effectiveness of the efficiency improvement in Louisiana.

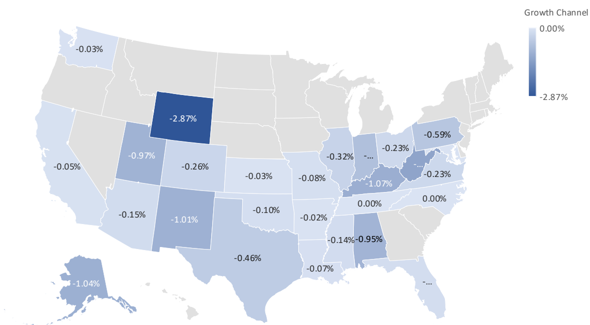
There are a few important insights to take away from this exercise. First, the results of the simulation show energy savings from the price, growth, and composition channels vary widely across regions. For example, in some states, I find fuel prices increase following the energy efficiency shock, which improves the overall effectiveness of the efficiency improvement. However, I also find fuel prices may decline in some states from the efficiency improvement, reducing the improvement's effectiveness. Second, the reduction in energy savings from re-spending by households via the growth channel is typically large. This provides suggestive evidence that regional policymakers could improve the aggregate outcomes of energy efficiency improvements by enacting complementary programs that limit the impacts of these re-spending effects. Third, the composition channel dominates the other channels in each scenario. This characteristic of the results provides an explanation for why output elasticities are sensitive to the choice of elasticity of substitution. When input substitution is rigid, the input-output network changes in such way that the structural importance of the energy sector and other energy-intensive sectors declines, thus creating positive energy savings overall. However, when input substitution is flexible, the model predicts the energy sector and energy-intensive sectors become more central producers in the economy and energy use increases, holding prices and income fixed. When this occurs, the embodied energy of goods and services sold in the economy increases.



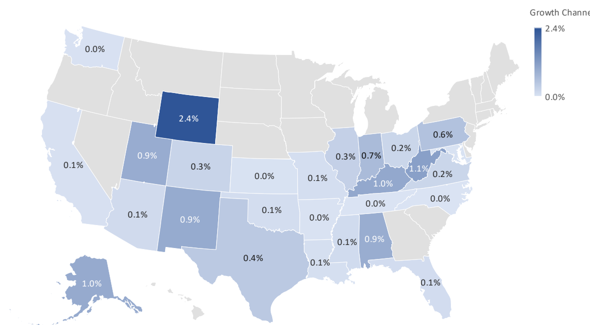
(a) Price Channel ($\sigma = 0.25$)



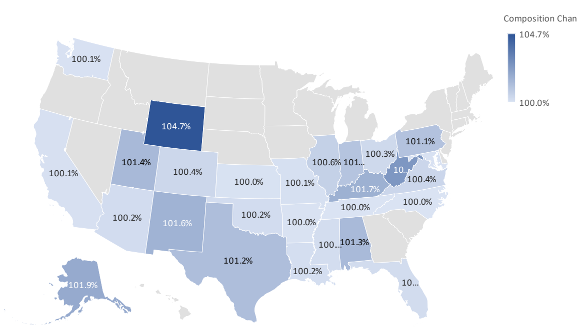
(b) Price Channel ($\sigma = 1.75$)



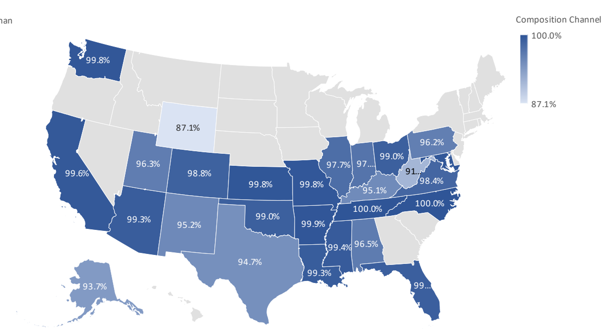
(c) Growth Channel ($\sigma = 0.25$)



(d) Growth Channel ($\sigma = 1.75$)

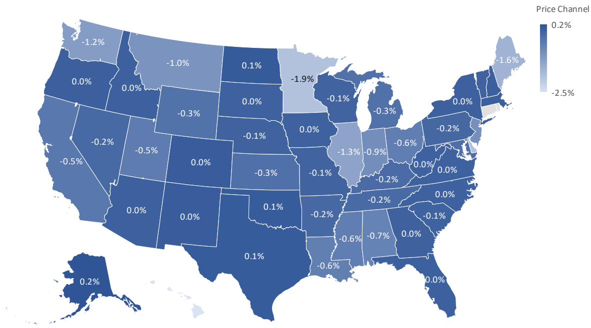


(e) Composition Channel ($\sigma = 0.25$)

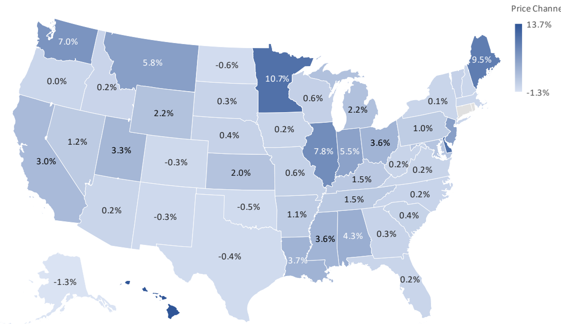


(f) Composition Channel ($\sigma = 1.75$)

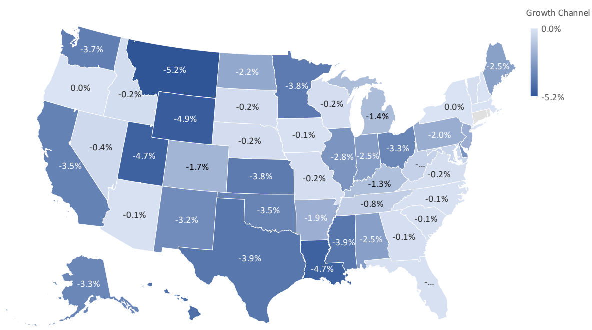
Figure 4.7: Coal Savings from Different Channels



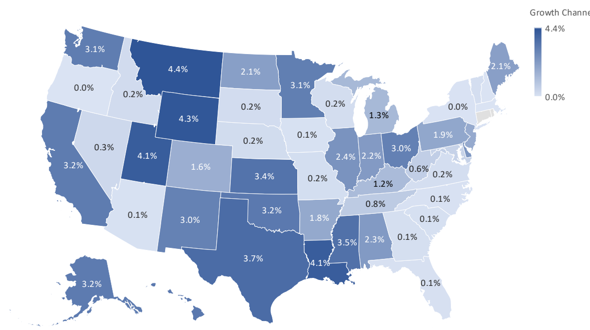
(a) Price Channel ($\sigma = 0.25$)



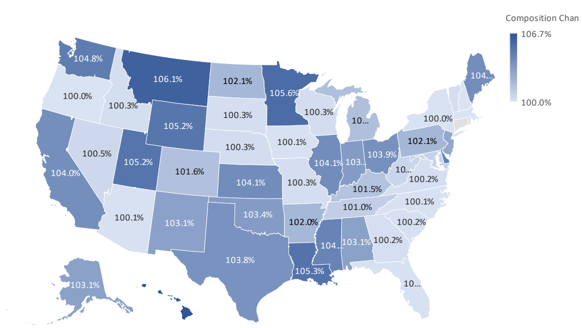
(b) Price Channel ($\sigma = 1.75$)



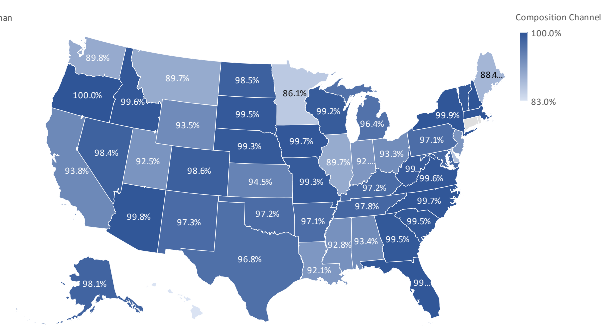
(c) Growth Channel ($\sigma = 0.25$)



(d) Growth Channel ($\sigma = 1.75$)

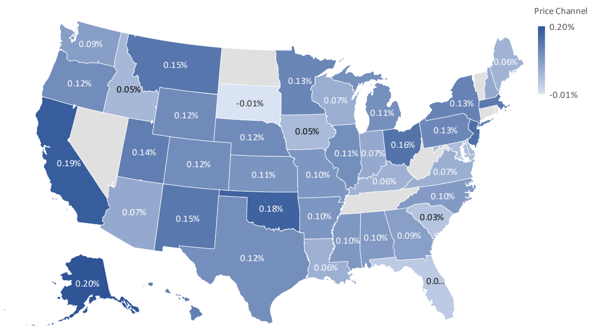


(e) Composition Channel ($\sigma = 0.25$)

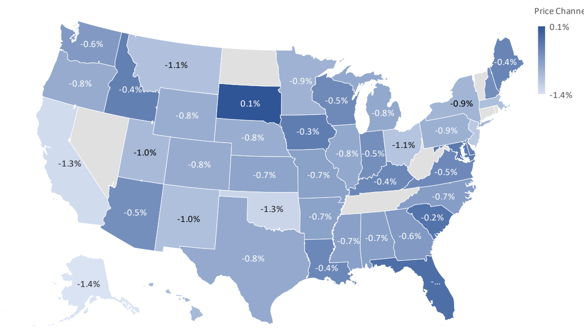


(f) Composition Channel ($\sigma = 1.75$)

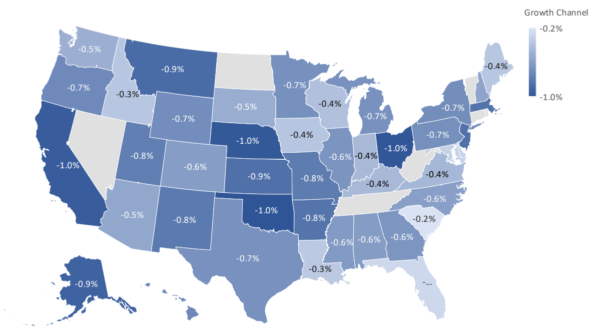
Figure 4.8: Oil Savings from Different Channels



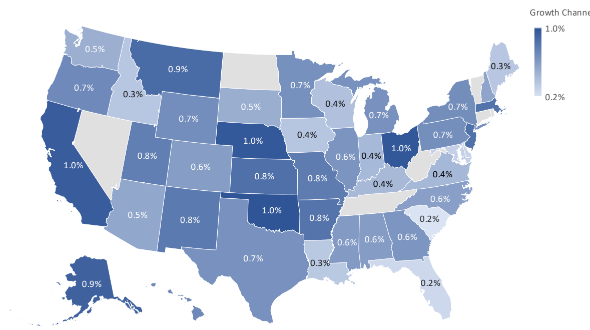
(a) Price Channel ($\sigma = 0.25$)



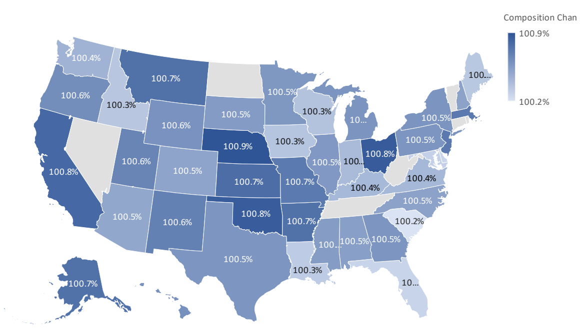
(b) Price Channel ($\sigma = 1.75$)



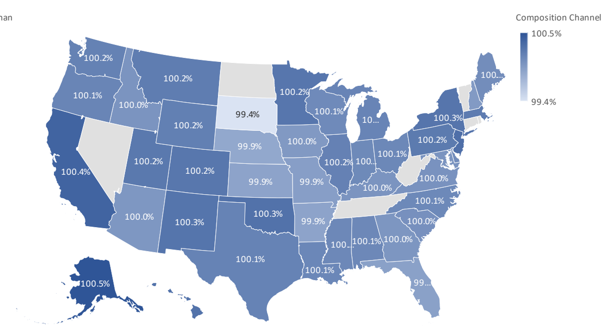
(c) Growth Channel ($\sigma = 0.25$)



(d) Growth Channel ($\sigma = 1.75$)



(e) Composition Channel ($\sigma = 0.25$)



(f) Composition Channel ($\sigma = 1.75$)

Figure 4.9: Gas Savings from Different Channels

Energy Savings Multipliers

In Section 4.5.3, in the absence of a production network, I show that maximal energy savings are achieved when efficiency improvements reduce fuel consumption in sectors that consume a large share of local energy resources. However, the impact of the composition channel on energy savings suggests the structure of industrial activity has important implications for how energy efficiency improvements are reflected on the aggregate level.

In this section, I explore the contribution of the production network to aggregate energy savings. In particular, I compute the energy savings multiplier (ESM) for each state and simulation scenario to illustrate how each economy's production network impacts the aggregate energy savings from an efficiency improvement. For the exposition, I will focus on discussing the impact of the economy's production network on energy savings for the rigid substitution scenario.

Figures 4.10-4.12 present the ESM by state and simulation scenario. In each scenario, the ESM is positive for each state but ranges between 0 and 1. Referencing Table 4.1, the value of the ESM has different interpretations for the rigid and flexible substitution scenarios. In the rigid substitution scenario, values greater than 1 imply network-driven energy savings are positive and push aggregate energy savings closer to the anticipated value. In contrast, when $0 < ESM < 1$, network-driven energy savings are negative, implying the economy's production network curtails the effects of the efficiency improvement. However, in this case, network-driven energy savings are not large enough to cause the efficiency improvement to increase overall energy consumption.

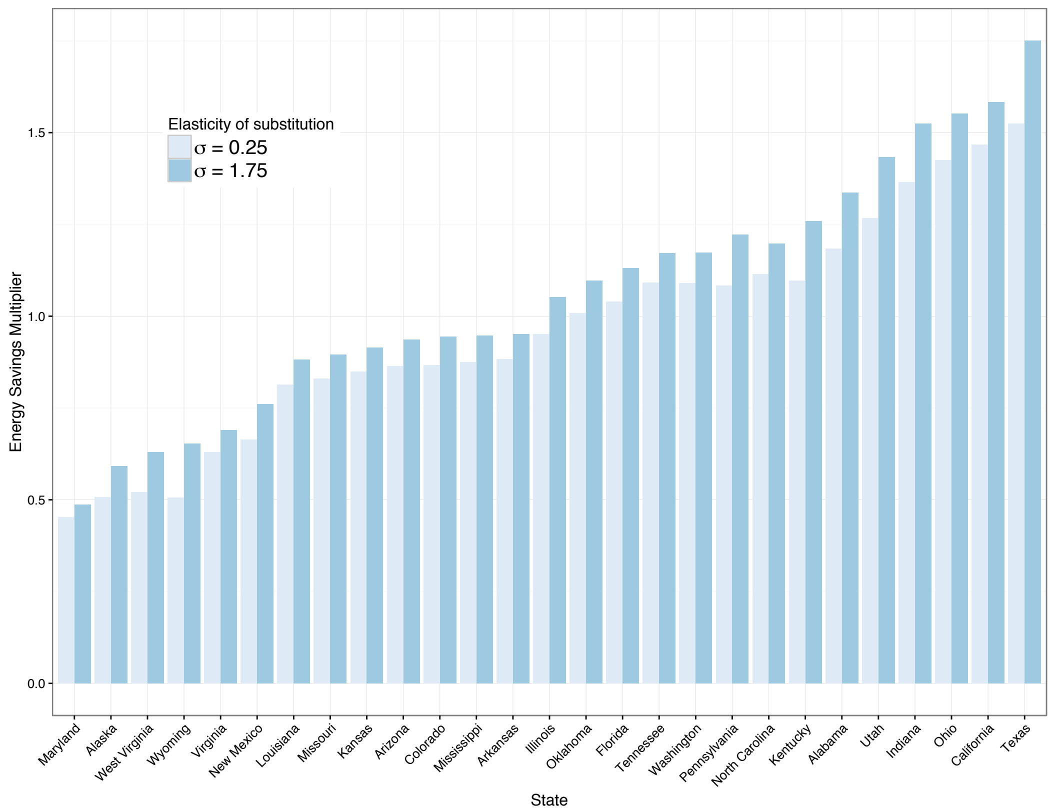


Figure 4.10: Energy Savings Multipliers for Coal Mining

Figure 4.10 presents the results from the coal simulation using the rigid and flexible substitution scenarios. The simulated ESM ranges between 0 and 1, but is strictly positive for each scenario. The states with the largest output elasticities, Tennessee, Texas, and Pennsylvania, all have ESMs greater than 1. This implies for every unit of direct energy savings the production network created an additional ESM > 1 units of savings. Hence, the production networks in these states create a positive multiplier effect for energy efficiency improvement. Wyoming was the state with the least effective energy efficiency improvement in this scenario, and I find the ESM for Wyoming is less than 1. This means that, for the same energy efficiency improvement, Wyoming only realizes a fraction of the energy savings because re-allocation within the production network curtailed the effects of the improvement.

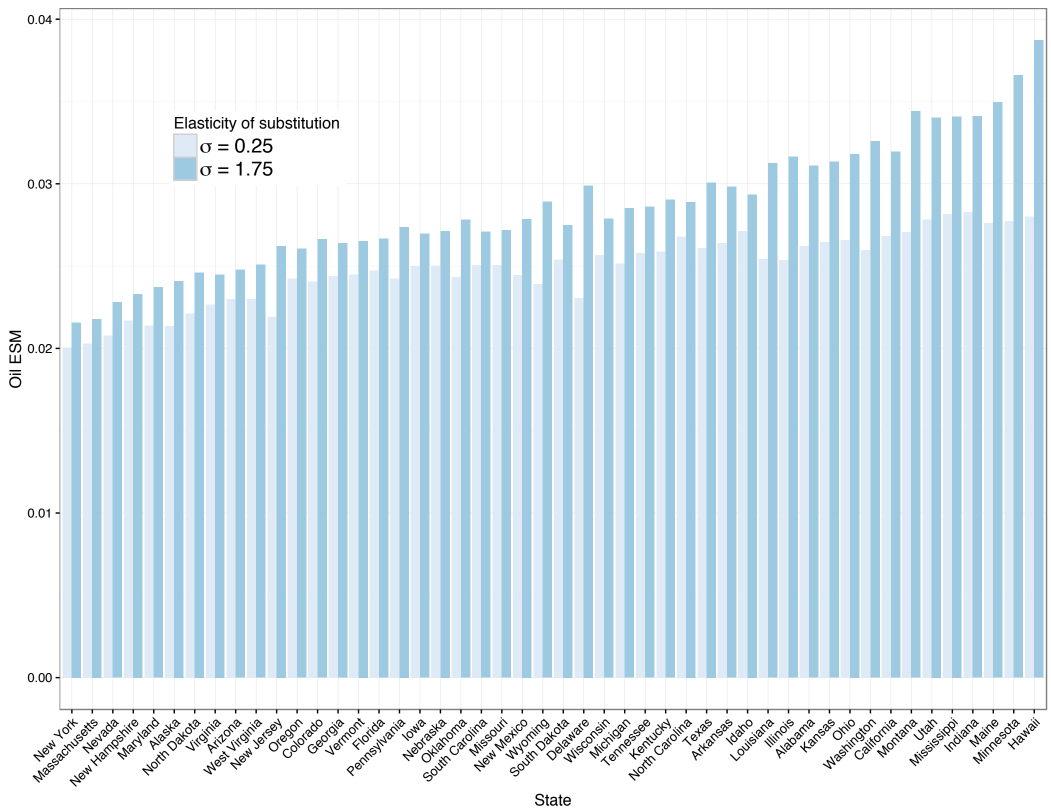


Figure 4.11: Energy Savings Multipliers for Petroleum Refineries

The simulated ESMs for the oil scenario are presented in Figure 4.11. Unlike the coal scenario, the values of the simulated ESMs are below 1 for each state. This implies the production network curtails the energy efficiency improvement at the aggregate level for each state. Moreover, the ESMs do not exhibit the same heterogeneity found in the simulated ESMs for the coal scenario. One possible explanation for this behavior may be the consequence of the structural similarity of the Truck Transportation sector across different states. If the systemic importance of Truck Transportation varies only slightly by state, then this would explain the lack of substantial heterogeneity in these results. I explore this in more detail in the next section.

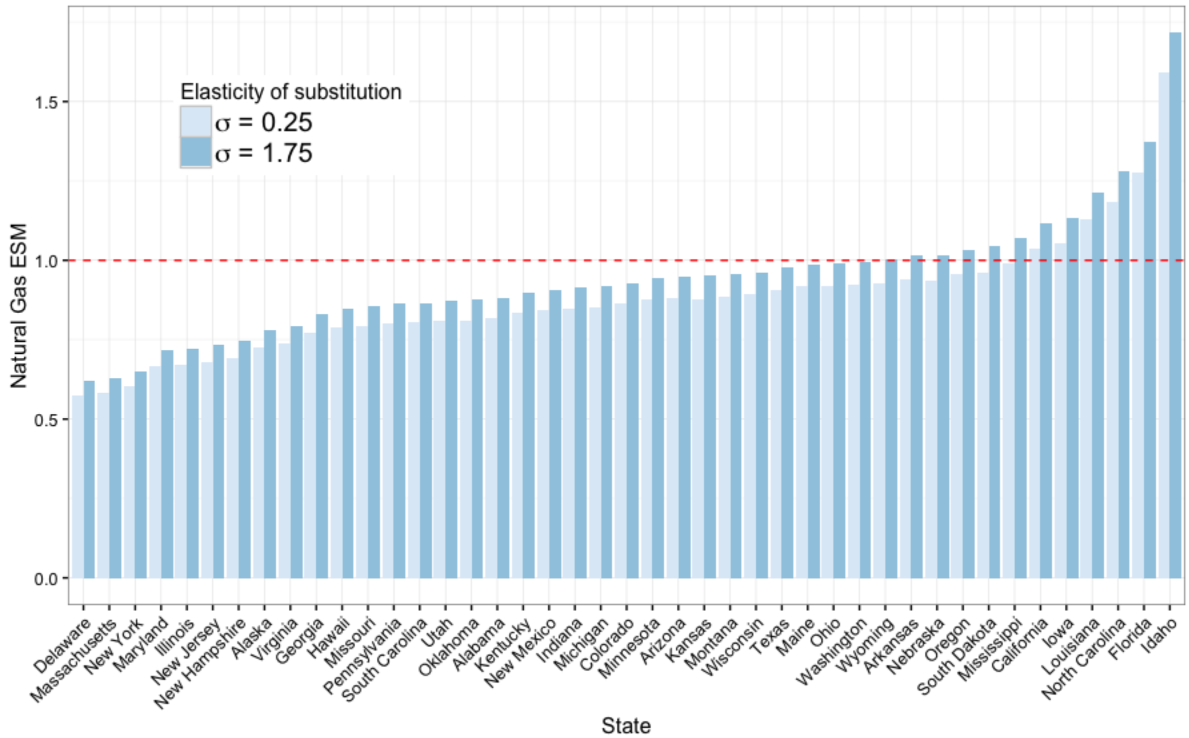


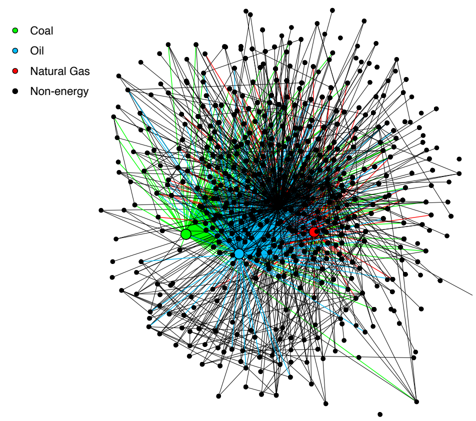
Figure 4.12: Energy Savings Multipliers for Natural Gas Distribution

Figure 4.12 displays the ESM results for gas simulation. Two of the states with the highest output elasticities, Louisiana and Idaho, have ESM values above 1. Ohio, the state with the third largest output elasticity, has an ESM slightly less than 1. The three states with the lowest output elasticities–Michigan, Indiana, and Virgina–have an ESM of less than unity. For the states with the lowest output elasticities, the production network contributes to a reduction in aggregate energy savings, implying the micro-scale efficiency improvement would have resulted in a higher output elasticity in the absence of a production network.

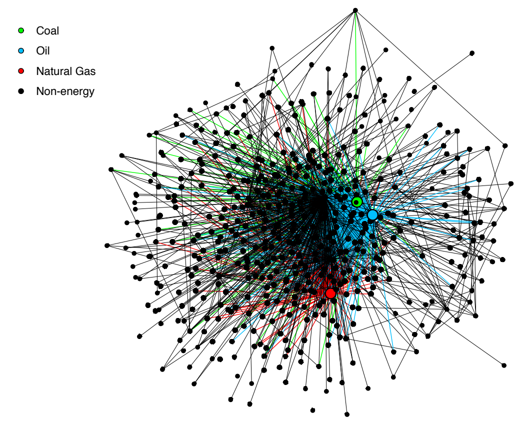
Energy Savings Multiplier and Network Characteristics

Throughout the paper, I claim that heterogeneity in the structure of production networks can explain differences in aggregate outcomes following micro-scale energy efficiency improvements. In this section, I summarize some important features of the regional input-output networks used in the simulation to show heterogeneity exists across these production networks. Moreover, I illustrate the upper tail of the supplier centrality distribution exhibits scale-free behavior [169]. The scale-free behavior in the upper tail of the distribution suggests the presence of a few “hub-like” sectors in each regional production network. These hub sectors are major suppliers, both directly and indirectly, in the economy’s production network and are thus “systemically important” for production. Importantly, prior research has shown that shocks occurring in these hub sectors lead to larger fluctuations in aggregate performance [175, 176].

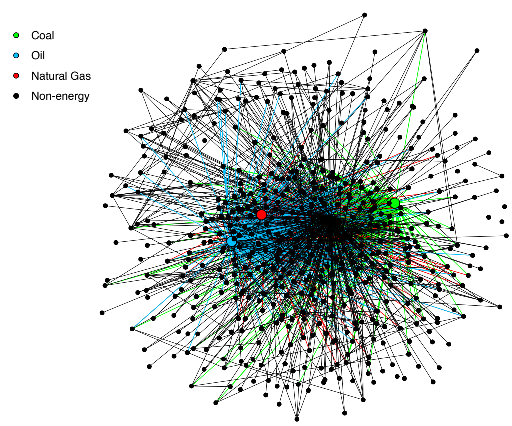
In the context of how energy efficiency improvements aggregate into economy-wide energy savings, the same sector in two different regions may serve vastly different functions, and thus vary in terms of systemic importance. This potential heterogeneity in the structural importance of the source sector may factor into how production networks interface with micro-scale energy efficiency improvements. I provide evidence to affirm this hypothesis. Specifically, I illustrate the supplier centrality of the source sector correlates with that sector’s response to the efficiency shock. Moreover, I show this correlation carries over to explain the size of a state’s ESM from the simulation. I find source sector’s with a higher supplier centrality are associated with higher ESM values. This finding implies efficiency improvements occurring in systemically important sectors generates higher energy savings through the production network.



(a) California



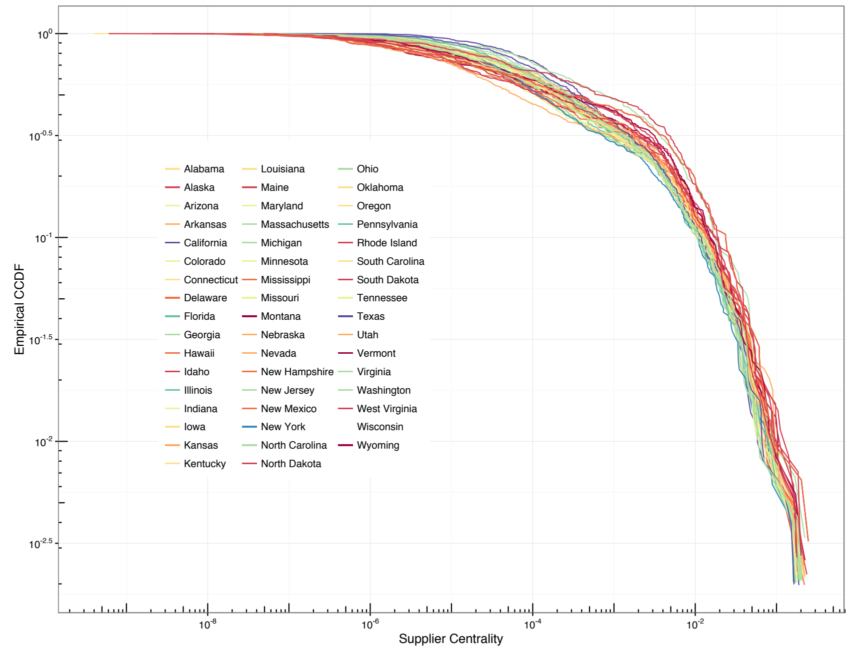
(b) Pennsylvania



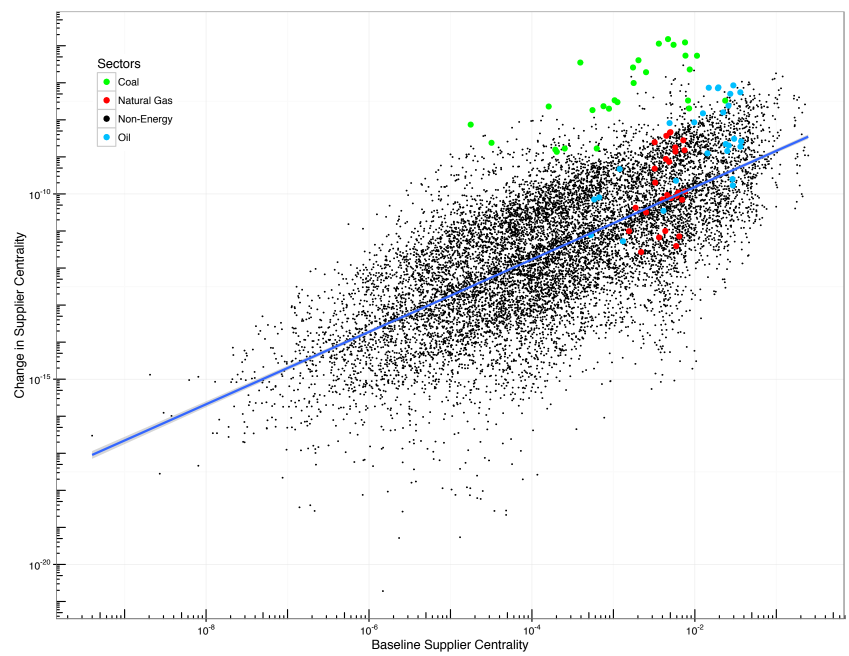
(c) Texas

Figure 4.13: Examples of calibrated input-output networks

Figure 4.13 visualizes three production networks calibrated from the IMPLAN input-output data. Each node in the network corresponds to a sector and the size of the edges are proportional to the direct requirements coefficients of the industries. Energy industries are colored-coded, while non-energy producing sectors are black. I use the Fructerman-Reingold algorithm to visualize the production networks. The visualization helps to illustrate some of the structural features of production across different regions, and, particularly, the structural role of the energy sector in these regions.



(a) Empirical counter-cumulative distribution functions by state



(b) Change in Supplier Centrality

Figure 4.14: Empirical Counter Cumulative Distribution Function (CCDF) and Change in Supplier Centrality

A more complete characterization of regional production structures is given by the illustrations in Figure 4.14. Figure 4.14a plots the empirical counter-cumulative distribution function (CCDF). The empirical CCDF of supplier centralities gives the probability of observing a supplier centrality greater than or equal to some threshold value. A notable feature of these distributions is that the supplier centralities span several order of magnitude, and the distribution exhibits an approximate linear relationship observed in the upper tail of the distribution. This linear relationship is indicative of the presence of a few "hub-like" sectors, capturing the disproportionate role of these sectors as input suppliers in the economy.

I plot the change in a sector's supplier centrality as a function of the sector's baseline supplier centrality in Figure 4.14b. For the visualization, I plot the results from the efficiency shock applied to coal, but the results are comparable for other shocks. The observations are plotted on a log-log scale so that the scale of the x-axis corresponds to the same scale in 4.14a for comparison. The change in supply centrality spans several orders of magnitude and reveals substantial disparity in a sector's exposure to a shock. The linear relationship, in particular, reflects the notion that more central sectors, as measured by the sector's Bonacich centrality, are more exposed to idiosyncratic shocks in the economy. Figure 4.14b also illustrates the heterogeneity in the role of energy as a supplier of inputs across different regions. The supplier centrality for the Coal Mining sector, for instance, spans several orders of magnitude; whereas, the supplier centrality of the Natural Gas Distribution sector tends to cluster relatively around a common value. Petroleum refineries tend to occupy a more central position in regional production networks with only a few exceptions.

Figures 4.15-4.17 plot the relationship between the simulated ESMs and the supplier centrality of the source sector. These figures highlight how the systemic importance of the source sector varies across states and how this systemic importance translates micro-scale energy efficiency improvements into aggregate energy savings. Across each scenario, the figures reveal a positive relationship between the source sector's supplier centrality and the simulated ESM. When energy efficiency improvements occur in systemically important sectors, the production network will generate additional energy savings. Because of this, energy efficiency improvements occurring in sector's with higher supplier centralities tend to result in higher output elasticities at the aggregate level.

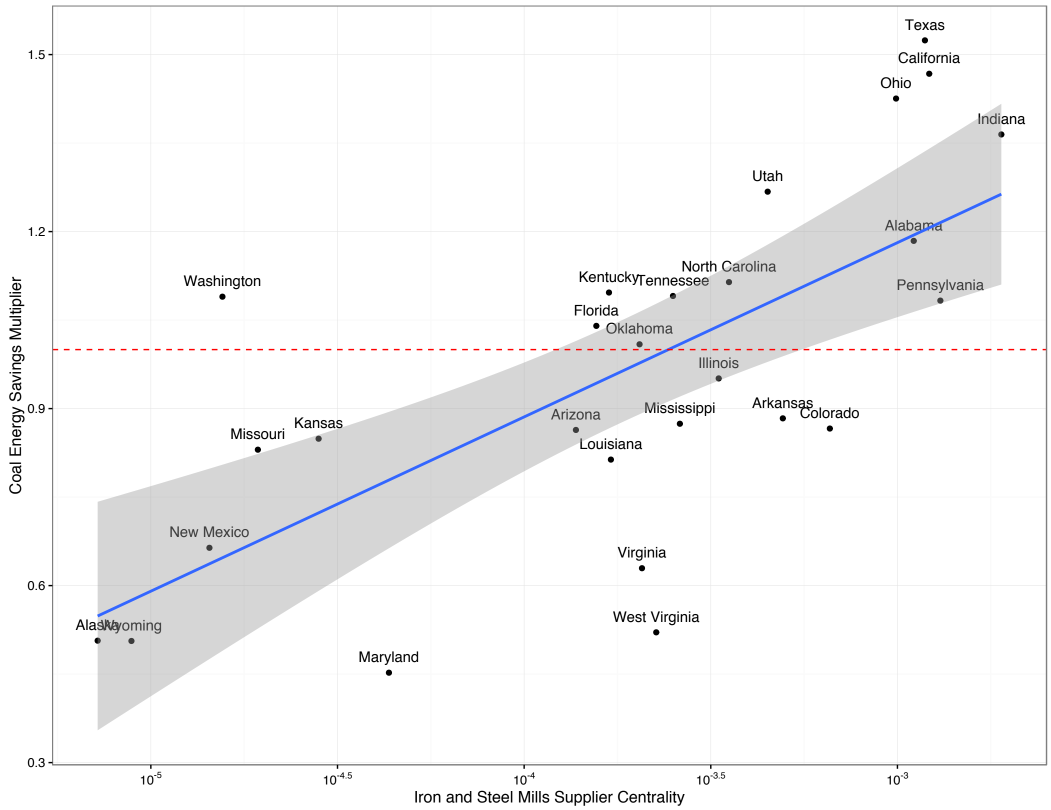


Figure 4.15: Coal ESM and Iron and Steel Mill Supplier Centrality

In the coal simulation, the supplier centralities of Iron and Steel Mill Manufacturing in Texas and Pennsylvania are among the highest across all states. Figure 4.15 suggests the structural importance of these sectors determines the magnitude of the ESM for these states. In contrast, Wyoming, Alaska, and Missouri have the lowest output elasticities (in absolute value) in the coal simulation. I find Iron and Steel Manufacturing in these states plays a much more insignificant role as an intermediate input supplier to these local economies. In particular, the supplier centrality of Iron and Steel Manufacturing in these states is around two orders of magnitude below Texas and Pennsylvania. My findings

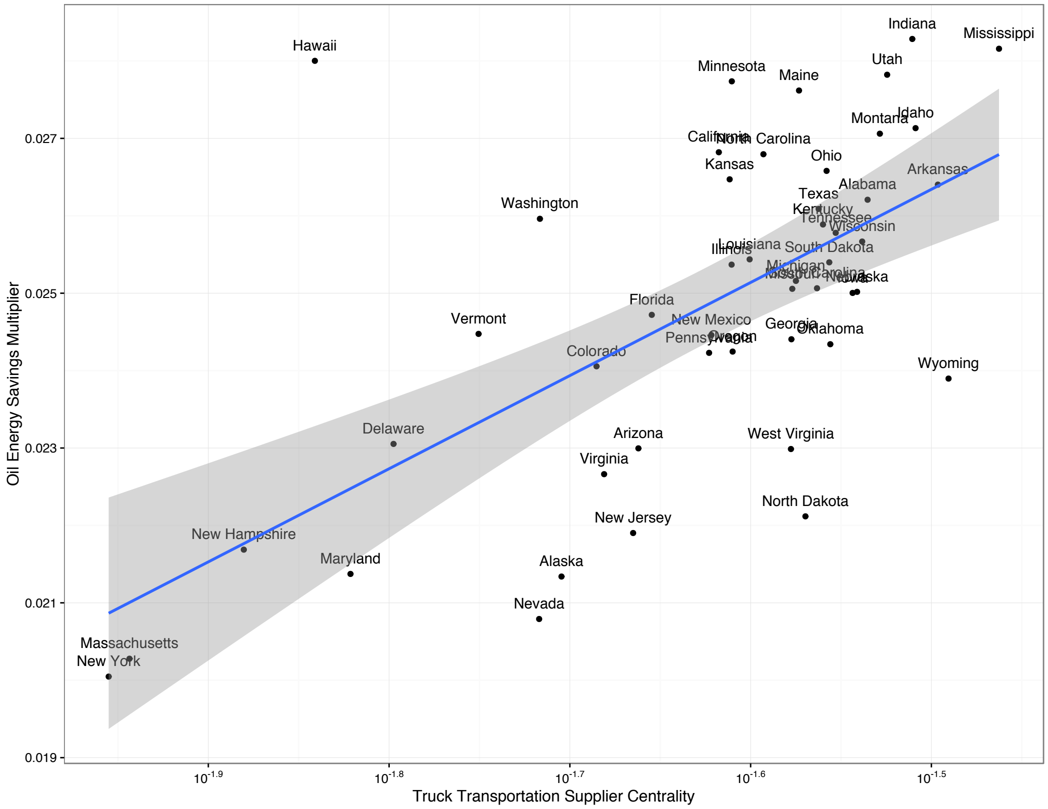


Figure 4.16: Oil ESM and Truck Transportation Supplier Centrality

suggest the structural importance of these industries can explain why these states have the lowest output elasticities.

I find a similar relationship holds in the oil simulation. In particular, the states with the largest output elasticities also tend to have source sector's with larger supplier centralities. However, the structural importance of the Truck Transportation sector does not vary substantially across states. Unlike the coal simulation, where the supplier centrality of Iron and Steel Manufacturing span several orders of magnitude, the supplier centrality of the Truck Transportation sector tend to cluster around a similar value. This explains why the simulated ESM for the oil scenario does not reveal substantial heterogeneity across states. Despite this, I find larger ESM values are associated with states where Truck Transportation is more systemically important to the local economy. This is evident from the positive relationship between the ESM for oil and the Truck Transportation supplier centrality depicted

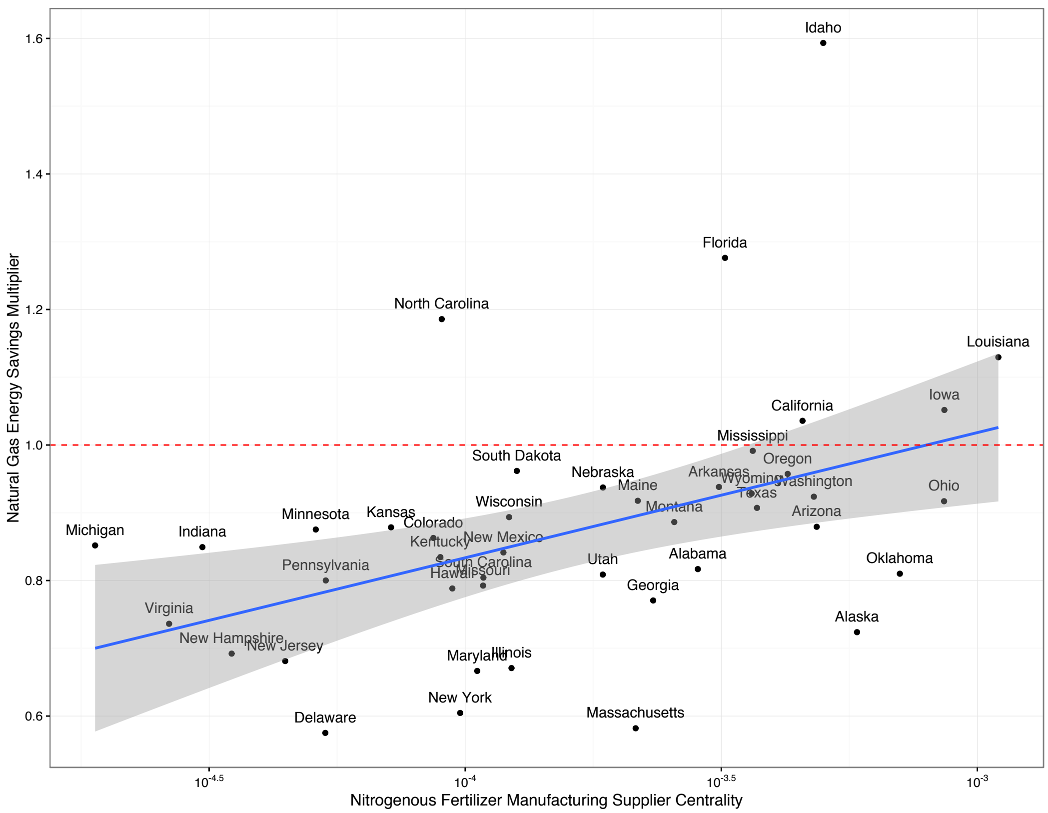


Figure 4.17: Natural Gas ESM and Nitrogenous Fertilizer Manufacturing Supplier Centrality

in Figure 4.16.

Figure 4.17 illustrates the relationship between the simulated ESMs for the gas scenario and the supplier centrality of the Nitrogenous Fertilizer Manufacturing sector for each state. The supplier centrality of the Nitrogenous Fertilizer Manufacturing sector is largest in Louisiana, the state with the largest output elasticity for the gas scenario. In contrast, the Nitrogeneous Fertilizer Manufacturing sector in Michigan has the lowest supplier centrality. Michigan has the lowest output elasticity in the gas scenario. I find the positive relationship between the ESM and the source sector's supplier centrality holds for the gas scenario. States where the Nitrogeneous Fertilizer Manufacturing sector is more essential for the supply of inputs to the local economy experience additional energy savings generated by the existence of the local production network.

4.7 Conclusion

Energy efficiency improvements in micro-scale energy services, such as heating, lighting, and transportation, have enabled more productive use of available energy resources. However, over the past century, the modest reductions in global energy intensiveness indicate the magnitude of these micro-scale energy efficiency improvements do not always bear out on an aggregate scale. The past century has also given rise to a substantial change in the organization of production. Production processes have become increasingly fragmented and characterized by complex, interconnected supply chains of specialized input suppliers. This shift to a networked organization of production may have important implications for how micro-scale energy efficiency improvements materialize on an aggregate level.

In this paper, I investigate how industrial energy efficiency improvements interface with production networks to determine aggregate energy savings. Energy efficiency improvements increase a producer's capacity to convert energy resources into useful energy services. As producers adjust their inputs in response to the efficiency improvement, the efficiency shock transmits to other industries via the input-output linkages captured by the economy's production network. The transmission of the efficiency shock through the production network induces other producers to adjust their input mix, causing additional adjustments in commodity and factor markets in the economy. As a consequence, I show the economy's production network creates additional aggregate energy savings or losses through a price, growth, and composition channel.

Using detailed state-level input-output tables, I simulate a 10% energy efficiency improvement and evaluate the contribution of production networks to overall energy savings. My results suggest production networks can either contribute additional energy savings or detract from overall energy savings. In some instances, I find production networks increase aggregate energy savings by more than 60%, but in other cases, I find the production network reduces energy savings by almost 100%. I show the magnitude of these contributions is positively related with the structural importance of the sector experiencing the energy efficiency improvement. Importantly, the structural importance of a sector is directly captured by the sector's Bonacich centrality, a well-defined network centrality statistic. Efficiency improvements occurring in sectors with higher Bonacich centralities translate into higher aggregate energy savings in the presence of a production network.

My findings are important for designing effective industrial energy efficiency policy in an interconnected world. In particular, my findings suggest a heterogeneous policy mix could achieve better policy outcomes. By taking the model to data, I find energy efficiency improvements are most effective when they occur in sectors of systemic importance to the local economy. Under the right conditions, targeting systemically important industries leads to a structural transformation of the economy toward less-energy intensive goods and services, creating a multiplier effect for energy savings. Moreover, I show this multiplier effect correlates with a well-defined measure of network centrality. By utilizing this relation, policymakers can improve policy outcomes by adjusting interventions to target efficiency policy at more central sectors in the local economy.

Although the model in the paper is static, the primary results of this study provide important insights for the dynamic implications of energy efficiency policy. Specifically, I show that energy efficiency policy can lead to adjustments in the economy's production network, changing the structural importance of certain industries in the economy. If substitution between energy and non-energy inputs is sufficiently flexible, the production network can potentially evolve toward energy-intensive goods and services, strengthening the systemic importance of the energy sector over time. The evolution of production systems toward energy-intensive process may create additional inertia within already entrenched fossil fuel based energy systems. Given modern production systems are continuing to become highly fragmented and transnational, counteracting the inertia introduced by a global production network will require a coordinated global effort to reduce global energy intensiveness and avoid environmental catastrophe.

CHAPTER 5
CONCLUSION

This dissertation reflects on strategies for utilizing networks to catalyze a low-carbon energy transition. In particular, I focus on the role of networks for two policy strategies: (i) switching to alternative, low-carbon energy technologies, and (ii) reducing consumption of carbon-intensive, fossil fuel energy resources. Chapter 2 of this dissertation uses historical energy transitions to argue networks complicate prescriptive policy design. In particular, we illustrate the nature of the underlying technologies used to covert physical fuel inputs into energy services structures interactions between markets. The interconnections between markets, in turn, creates complex feedback loops that lead to simultaneous changes across the entire economy. We explore how these feedback loops impact energy efficiency policy in more detail in chapter 4. Chapter 3 investigates the role of networks in proliferating the diffusion of low-carbon energy technologies. We provide evidence that network formation is critical for the early success of emerging low-carbon innovations. When networks form at this early stage of the technology life cycle, they provide a platform for information exchange between early and future adopters, leading to lower search, transaction, and operational costs for future adopters. Lastly, in chapter 4, we develop a theoretical model that embeds industrial, energy efficiency improvements within a network setting to understand how interconnections between markets affects the outcomes of sector-specific low-carbon energy policy. Energy efficiency is often touted as a cure-all policy measure to reduce dependence on carbon intensive, fossil fuel resources. However, when markets are connected by the economy's production network, the outcome of energy efficiency policy is highly uncertain. Using a combination of theoretical and numerical analyses, we illustrate the structure of the economy's production network shapes the change in aggregate energy consumption following a sector-specific energy efficiency improvement.

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